Metaphorical Representation in Design and Dance Teaching in Higher Education Art Studies - Based on Affective Computing Analysis

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Abstract: To gain a more comprehensive understanding of students' affective experiences in designing and teaching artistry and dance in higher education, and to understand the role of metaphorical expression in dance learning. In this paper, we utilize affective computational analysis to capture students' affective experiences from dance instruction, using body movements and facial expressions to identify and categorize students' affective states in dance instruction. A better understanding of students' emotional experiences is achieved by collecting affective data, including affective intensity levels, affective dimensions, and basic features of basic emotional expressions. In terms of emotion feature extraction, Mel frequency cepstrum coefficients, convolutional neural networks and long and short-term memory neural networks are applied to extract the emotional features exhibited by students in dance teaching. Finally, unsupervised classifiers are integrated to construct an emotion computation model to help teachers and students in the field of design and dance teaching in college art studies to better understand, express and apply metaphors. The analysis found that the efficiency of emotion transfer reached 100%, and the difference between the scores of the control group and the experimental group was slightly close to the significance level $P<0.10$. The construction of emotion is expected to provide useful insights for educational practice and instructional design, and to enhance the effect and experience of teaching Artistic Design and Dance in colleges and universities.
Keywords: artology design; dance teaching; emotion calculation; Meier frequency; convolutional neural network

1. INTRODUCTION

Metaphor is a fundamental feature of human thought and an important cognitive phenomenon, as a reasoning activity founded on similarities between different semantic fields, metaphor maps from a concrete conceptual domain to an abstract conceptual domain (Orifjonovich, 2023). Since art originated from schematic metaphors, both plant and animal forms and hieroglyphics that convey ideas have some kind of metaphorical function, and it is obvious that this is the earliest and most basic function possessed by ancient schematic artifacts (de Saint Preux & Blanco, 2021). It can be said that the metaphors of art express the subject's artistic ideas indirectly through correspondence. The abstract nature of human thought makes all kinds of metaphorical expressions in the development of art language-conveyance of ideas, perception of thoughts and concern for the present. In the wave of free and diversified development of contemporary art, metaphor is a sensitive and complex topic. Whether it is easel painting, art design world or dance teaching, every artist, in stating his or her own ideas, more or less permeates his or her metaphorical connotation in the expression of works, such as what he or she tries to do, what he or she is thinking about, what revelations are brought by his or her cultural background, and what kind of meanings he or she wants to lead the viewers to feel (Kini-Singh, 2023). In any case, as both artists and viewers, it is hoped that all artists, like all artists, can accurately express and comprehend the connotations and deep meanings of their works (Kodirova, 2020).

Since existing research has not yet proposed a systematic computational method for teaching in colleges and universities, this paper aims to bring new perspectives and methods to dance teaching, and to assist teachers and students in developing emotional communication and creativity. In the design of art studies and dance teaching in colleges and universities, this paper utilizes affective computational analysis methods to collect students' affective data, such as affective intensity levels, affective dimensions, and basic characteristics of basic affective expressions, to accurately understand students' affective states in dance teaching. Secondly, it focuses on the basic features of emotional intensity level, emotional dimension and basic emotional performance, and then explores the metaphorical expression forms therein. The patterns and paths of metaphorical expressions are further explored by applying the Mel frequency cepstrum coefficient, convolutional neural network and long and short-term memory neural network. Finally, the individual innovative elements are integrated by constructing an affective computing model. The proposed method will help teachers and students to better understand, express and apply metaphors, providing innovative perspectives and approaches in dance learning.

2. LITERATURE REVIEW

Regarding the use of metaphors in the design of campus artistry, Shakoury, K et al. surveyed students at a Canadian university about their perceptions of multiculturalism and multicultural societies in order to describe metaphors for these concepts to understand (Shakoury & Boers, 2024). It was found that students tended to use metaphors related to diversity and integration, such as a wide variety of arts/crafts, rather than metaphors related to assimilation. It was also found that participants varied in their awareness of their use of metaphors, but that reflection on metaphors helped to increase students' level of awareness. Stampoulidis, G et al. noted that current research on image metaphors and other rhetorical devices focuses on the field of advertising, while there is a relative dearth of other types of research (Stampoulidis & Bolognesi, 2023). The study used a corpus of 50 street art works and analyzed metaphors and other rhetorical devices in these works. Qualitative analysis showed that successful interpretation of these images often requires the integration of conceptual, contextual, socio-cultural, and linguistic knowledge. Catalano, T et al. presented an application of the arts and community proximity methodology for multicultural teachers, in which 24 ex-teachers and 5 adult Yazidi refugee community members participated in this study (Catalano et al., 2021). The research materials consisted of transcripts of the pre- and post-group discussions, as well as oral and written transcripts from the week following the workshop. A metaphorical approach was used to investigate how participants in the program talked about their experiences during the workshop, and the acb method is expected to be a multicultural development tool for teacher education.

The role of metaphors in dance teaching has also been suggested by research, with Reed, D. J proposing a deeper understanding of the material, sensory, process and experiential potential of digital data relationships through the development of a dance metaphor (Reed, 2020). The study applied Blumer's concept of sensitization and the theory of communicative dance to the everyday use of the Apple Watch in order to advance research on the subtle interactive features of the device. Engelsrud, G et al. investigated the experiences of teachers and students in teaching creative dance in Norwegian school physical education placements (Ørbæk & Engelsrud, 2021). The study was conducted from a phenomenological perspective based on the concepts of participatory meaning-making, embodied emotion and embodied interaction as a basis for exploring students' experiences when interacting with their peers. The study focuses on the ways in which students interact with their peers during creative dance instruction and the implications of these experiences for the teaching of creative dance in sport . Abrahamson, D discusses the role of metaphors in the learning of physical skills.Previous research has focused primarily on the effectiveness of metaphors in providing actionable instructions in movement planning (Abrahamson, 2020). However, from a phenomenological, ecopsychological, and behaviorist perspective, action and perception are intimately linked, and metaphor-based learning models emphasize the moderating role of sensory activity in motor behavior.

Thus, metaphors are redefined as sensory constraints that are imaginatively projected in people's perception of action. This idea is supported by analyzing two examples of metaphors in a video on teaching cello technique, where the sudden effects of metaphors on target sensations are potential.

Regarding the use of affective computing in the design of campus artistry, Varner, E emphasizes the strong connection between music in general and social and emotional learning, which encompasses a range of social, emotional, behavioral, and character competencies that are necessary for success in school, in the workplace, in relationships, in the community, and in life (Varner, 2020). For example, activities such as improvisation, ensemble playing and singing, as well as ways of expressing emotions through music, can be used to develop social and emotional learning skills in the general music classroom. Drigas, A et al. explored the validity of metacognitive aspects such as cognitive competence, emotion regulation, and behavioral control, and a growing body of research suggests that unconscious processes may play an important role (Drigas et al., 2022). Different subthreshold training techniques were searched for and categorized, and the usability of ICTs for subconscious learning and training was assessed, e.g., artificial intelligence, virtual reality, mobile apps, etc.

Many other scholars have examined the use of affective computing in dance instruction, Borowski, T. G showed that social and emotional competencies are critical for success in school and life, including the ability to interact with others, regulate emotions and behaviors, solve problems, and communicate effectively (Borowski, 2023). Practice has shown that dance experiences can promote social-emotional development, and 110 articles on dance and SEC were reviewed to gain information on the theoretical development of how dance contributes to changes in SEC. Self-suggestion, nonverbal expression and communication, embodied cognition and learning, synchronicity, and supportive learning environments have been identified as key components of dance practice that help to promote SEC. He, Y addressed the fact that traditional dance teaching methods have time and place constraints and perform poorly in terms of resource management (He, 2022). Therefore, this study proposes a cloud-based dance teaching resource management system. The functional structure of the system includes core cloud computing teaching and teaching management applications. The data management module stores processed data in data files and is able to respond to retrieval requests from the dance teaching content distribution module and remote image resource location requests from the multimedia management module. The existing dance teaching resources are utilized for learning by designing the on-demand process of user courseware.

3. SENTIMENT CALCULATION ANALYSIS METHOD

3.1 Emotion Recognition and Classification

In the teaching of art design and dance in colleges and universities, body movements and facial expressions together constitute nonverbal behaviors of emotional interaction (Guol, 2023; Zhang et al., 2022). Compared with facial expressions, body movements are more diverse and express more complex and rich emotions. Using affective computing techniques, it is possible to identify and categorize the emotions generated by students during the learning process. This includes recognizing the type of emotion, such as happiness, anger, sadness, and joy, as well as the intensity of the emotion and emotional tendency (Järvelä et al., 2020; Savchenko et al., 2022). The metadata for visual emotion recognition and analysis is taken from videos of facial expressions and body movements, and then undergoes feature extraction, classifiers, and expression or movement recognition, respectively, to fuse the modal information from both the facial and body aspects, so as to more accurately and completely co-represent and analyze the learner's emotions in the learning process. Based on this, this study constructs a bimodal education visual emotion recognition model, obtaining learner images from the physical classroom on the left side, then extracting facial expressions and body movements, each into a different emotion recognition module, and finally combining the two to make a comprehensive analysis of the learner's emotions, and the visual emotion recognition model is shown in Fig. 1 (Middya et al., 2022). If the data sources are further extended to audio, video, self-report, trajectory of interaction and so on, then it will constitute a multimodal education visual emotion recognition model (Liu et al., 2021).

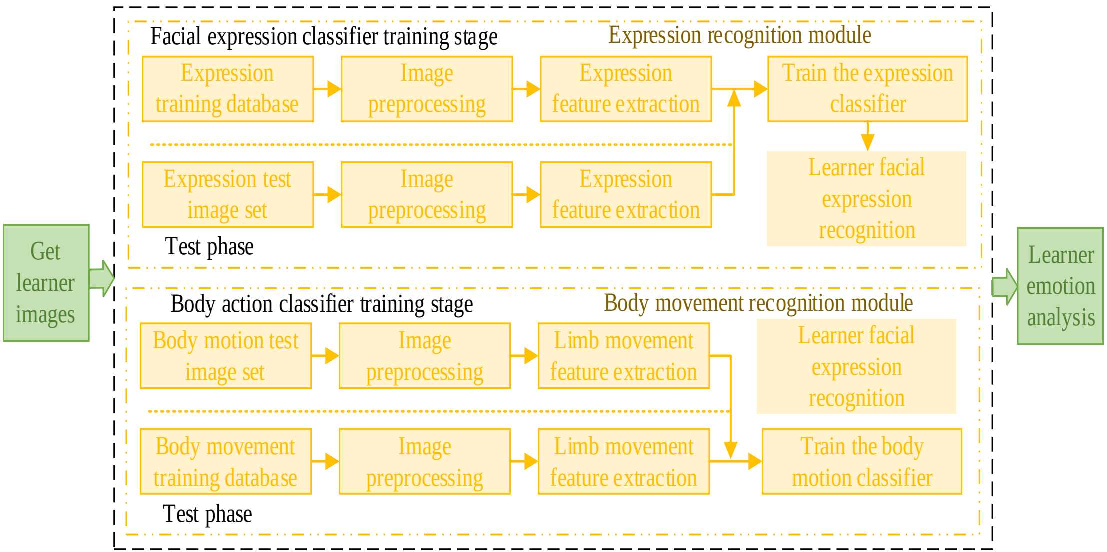

Figure 1: Visual emotion recognition model

3.2 Affective data collection

3.2.1 Emotional intensity levels

There is a distinction between high and low level of expression of emotion by body movement, if the expressive body movement is made to reach a certain artistic high. In terms of emotion, choreographers should try their best to show the degree of emotional change (Sagiv et al., 2020). Human emotions are first distinguished from the category, the ancient so-called seven emotions, Confucianism as joy, anger, sorrow, fear, love, evil desire, Buddhist as joy, anger, sorrow, fear, love, hate, desire. In modern psychological research, generally regarded as the basic emotions of joy, anger, sadness and fear, emotional intensity level as shown in Table 1. Dance bias guide makes the dancer form in the expression of emotion, should try to show the changing state of emotion. Because the design of artistry is complex and changeable, not solid and unchanging, the lyricism and expression of emotion is presented as a process of movement and change (Miao, 2020).

Joy or anger can develop from weak to strong in an augmentative way, or of course from strong to weak in an attenuative way. Correspondingly. Dancers should show the gradual increase or decrease of the character's emotion in the process of ups and downs, showing the change of the degree of emotion and the amount of the equivalent. The more explicit the physical movement is in the expression of the transverse unfolding of emotion, the more delicate and subtle the expression of the change of emotion is. For example, the choreographer of the dance skit "Jiang Cai Chang Ting" utilizes the different attributes of the movement, such as urgency, lightness, rigidity, flexibility, curvature, etc. to constantly increase the weight of the hurt feelings and express the upward trend of the emotions from weak to strong, and from less to more, constantly rendering the emotions to reach the maximum degree of saturation, and finally, in the embrace of two people will be the reluctance to part with the pain of the helplessness of the sketch in the best way possible. Because emotion can occur at different levels, can be caused by the sight, hearing, smell, taste, touch and other sensory stimulation of simple emotions, can also be caused by hunger, pain and muscle sensations related to simple emotions, these superficial emotions will sometimes be to the deep emotion transition (Menggo et al., 2021). Therefore, dancers' body movement cannot only stay in the expression of simple and superficial emotions, but should connect the expressed emotions with the deeper morality, will, and socio-cultural psychology of human beings, so as to deepen the depth of the expression of emotions in body movement. People's basic emotions are often not simple, sometimes entangled with other emotions, constituting multiple combinations and thus giving rise to many complex hybrid emotional forms, such as hate with love, anger and joy, envy and jealousy, etc. These complex emotions give rise to a richness of emotions. These complex emotions breed rich social content so that the emotions have richness and hierarchy (Roulet & Bothello, 2022). For example, in the dance drama "Death of Mingfeng", in her heart before she killed herself, both the grief of being forced to marry, but also the sweetness of love, Mingfeng is with her sadness, her despair, her love, her helplessness to throw herself into the lake. In terms of physical performance, the choreographer makes the dancer back her face and bite her hand, tilt her head and cover her face, bow her body and cry, smile and shake her head, etc., which reveals her complex inner emotion in the best way. Therefore, when the dancer's physical movement expresses these emotions, if the complex emotional content cannot be fully and three-dimensionally developed, it will not be able to let people fully appreciate the colorfulness of the emotions (Morejón, 2021).

Table 1 Levels of emotional intensity

Rank Class	Weak	Middle	Strong
Happy	Glad	Great rejoicing	Be wild with joy
Delighted	Sulk	Hit the roof	Rage
Sorrow	Be upset	Sadness	Deep sorrow
Fear	Afraid	Terror	Be in horror

3.2.2 Emotional Dimension

Emotions can be divided into four dimensions, emotional dimensions as shown in Table 2, the four dimensions have different combinations between them, such as excited pleasantness is happy and calm pleasantness is relaxed. This shows the fineness and richness of human emotions. The two poles of each emotion are not absolutely exclusive, but can be transferred to each other under the conditions of a certain situation. Such as joy and sadness, breaking down into laughter. A dance work is often a combination and interweaving of emotions of different dimensions and degrees. In addition human emotional reactions may be chronic sadness and anger, or phases of fury, or tensions such as cynicism, or acute outbursts of anger. Chronic states can be overridden by tense arousal, and tense states can be altered by acute reactions. Therefore, the design of artistry and the teaching of dance should show both the different dimensions of emotion and the different nature of emotional responses. Such expressive physical movement is clear and accurate. The character's emotional expression must be manifested in the movement of the form and move forward in the process of the movement of the form. Physical movement should be the inevitable development of emotion, and cannot be detached from the emotion and advance on its own. Structurally, emotion itself is characterized by movement, and the basic trajectory shows the process of stimulation-development-termination.

Table 2 Dimensions of emotion

Dimensionality	Implication	The Two Poles
Degree Of Certainty	The degree to which an individual is subject to emotion	Weak-weak
Hedonic Degree	The degree of pleasure and unpleasantness of an individual's subjective experience	Pleasant - not pleasant
Excitability	The suddenness of the emotion	Excitation-calm
Tensity	The activation level of emotion	Tension - ease

3.2.3 Basic Characteristics of Basic Emotional Expressions

In terms of physical movement, the choreographer should make the dancers' movements show the following contents, the accuracy of physical movement revealing human emotions. Generally speaking, different human emotions will produce corresponding physical movements, and there will be corresponding movement range and strength. Choreographers should let the dancers accurately reveal the inner emotions of the characters with the unique characteristics of physical movement. Table 3 shows the basic features of basic emotion expression, and the ethnicity of physical movement expression of emotion. The human body is the main carrier for preserving and expressing national culture, and dance movements inevitably show national cultural characteristics. That is to say, any expression of dance physical movement has ethnicity, in its unique physical movement parts and ways, high-frequency significant movements, movement strength, rhythm and so on, will have the sign of ethnicity. For example, in expressing joyful emotions, the Yi people fling their hands, turn their legs, swing their skirts, swing their feet in front of them, and have a fast rhythm. The Uyghurs move their necks, soften their wrists and rotate rapidly. The Mongolians are shaking their shoulders, softening their arms, with a soothing rhythm. This is the sensual manifestation of the cultural factors accumulated in the physical movement, such as aesthetic interest, national psychology, values, moral code, religious concepts, customs and other ethnic differences in the movement.

Table 3: Physical characteristics of basic emotional expression

Emotion	Basic Movement Of Form	Range Of Motion	Action Force
Happy	Lift your head, straighten your spine, open your arms, shake your hands, swing, undulate, jump and rotate your steps	Large amplitude of motion	Strong movement
Anger	Clenching fists, stomping feet, shaking, intramuscular tension	Large amplitude of motion	Strong movement
Sorrow	Head down, spine curvature, chest and abdomen retraction, striking the body, shaking, holding the head, kneeling		
Fear	Bend the head, bend the spine, close the shoulders, cross the arms, cross the legs and feet, bend the knees, curl the body, and shake the body	Low amplitude of motion	Weak movement

3.3 Emotional feature extraction

3.3.1 General framework

Based on the collected emotion data, emotion feature extraction is performed to transform the emotion information into a data form that can be understood by computers. Commonly used emotion features include the frequency of emotion words, the tone of emotion expression, and the use of emoticons. The overall framework of the proposed emotion recognition features is shown in Fig. 2, where the input speech data is first pre-processed by frame-splitting, windowing, etc. to obtain the Mel frequency cepstrum coefficients, which are then input into a convolutional neural network to extract the frequency domain features and short-time domain features. Then it is inputted into the long and short time memory neural network to extract the long time domain features, and finally realize the artistic design and dance emotion classification.

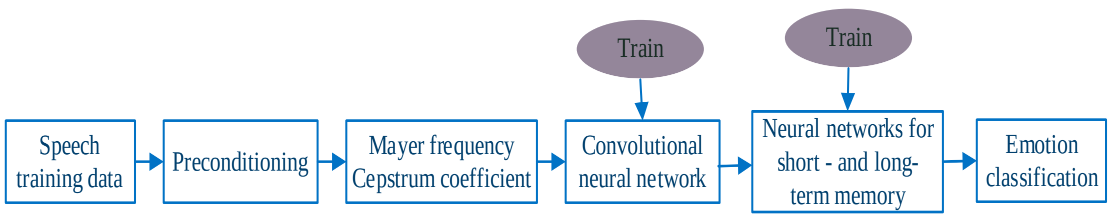

Figure 2: Overall framework of emotion recognition features

3.3.2 Mel-frequency cepstrum coefficients

Human beings perceive sound frequencies in different frequency bands differently. The perceptual ability of the human ear is linearly related to the frequency of speech in the low frequency band of speech, and logarithmically related to the frequency of speech in the high frequency band of speech. For the human ear in listening to different frequencies of speech will have different perception, thus proposed Mel frequency cepstrum coefficient.MFCC features in the Mel frequency and the ordinary frequency is a logarithmic relationship, and its expression is:

$$Mel(f) = 2951g(1+f/700) \quad (1)$$

In equation (1): f is the common frequency, Hz. $Mel(f)$ is the Mel frequency, and the process of extracting MFCC features is as follows:

(1) Pre-processing of speech and action signals, which includes pre-emphasis, frame-splitting and windowing, the pre-emphasis operation is actually to pass the speech signal through a high-pass filter as shown in equation (2) to highlight the resonance peaks at high frequencies, as the action signal is a short-time smooth signal, so the frame-splitting operation is performed to smooth the signal processing of each frame, and windowing of each frame signal is added in order to increase the continuity of the left and right ends of the frame. Assuming that the signal after the frame splitting is $s_n, n = 0,1,\cdots,N-1$, N is the frame size, the plus Hamming window is shown in equation (3).

$$H(Z) = 1 - \mu z^{-1} \quad (2)$$

In Eq. (2), μ is between 0.9 and 1.0, and 0.96 is selected.

$$s_n' = \left[(1-a) - 0.46\cos\frac{2\pi(n-1)}{N-1}\right]s_n \quad (3)$$

In Eq. (3), different a's produce different Hamming windows, which are taken as $a = 0.46$.

(2) A fast Fourier transform operation is performed for each analyzed window to convert the magnitude spectrum into a power spectrum by squaring, which is expressed as:

$$S_i(k) = \sum_{n=0}^{N-1} S_i(n) e^{-j2\pi k/N}, 0 \le k \le N \quad (4)$$

$$P_i(k) = \frac{1}{N}\left|S_i^2(k)\right| \quad (5)$$

Where $S_i(n)$ is the speech input signal, $S_i(k)$ is the amplitude spectrum, $P_i(k)$ is the power spectrum, and N is the number of points of the Fourier transform.

(3) The above spectrum is filtered through a Mel filter bank to obtain a Mel spectrum, which smoothes the spectrum and enables the elimination of harmonics.

(4) Since people's perception of sound and motion is not linear, a logarithmic operation is performed to analyze the spectrum with a nonlinear relationship.

(5) Discrete cosine transform is performed to obtain the cepstrum coefficients as follows:

$$MFVV_n = \sqrt{\frac{2}{N}} \sum_{k=1}^{M} \ln \theta(k) \cos\left[(k-0.5)\frac{q\pi}{M}\right], q = 1, 2, \cdots, L \quad (6)$$

In Eq. (6), $\theta(k)$ is the output energy of the k nd filter, L is the MFCC feature dimension, and M is the number of filters. The above principle of feature extraction is shown in Fig. 3.

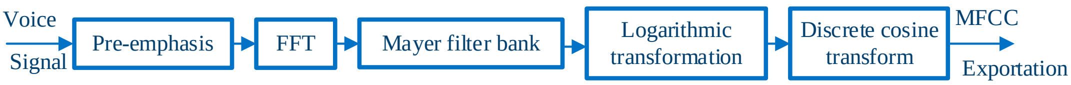

Figure 3: Principle of feature extraction

3.3.3 Convolutional Neural Networks

Convolutional neural network consists of convolutional layer, pooling layer, linear rectification layer and fully connected layer, and has the characteristics of local perception and weight sharing. Convolutional neural networks include one-dimensional, two-dimensional and three-dimensional convolutional neural networks, one-dimensional convolutional neural networks are often used in sequence data processing, two-dimensional convolutional neural networks are often used in image text recognition, and three-dimensional convolutional neural networks are mainly used in image and video data recognition. The convolutional layer consists of a number of filters, when the input to the model is a Mel Spectrum feature, the filter acts on the Mel Spectrum map, sharing its bias and weight, and then using convolution to extract the local features, the output of the convolution is the feature map. The key operation in the model is convolution:

$$(f*h)(t) = \sum_{K=-T}^{T} f(t)h(t-k) \quad (7)$$

In Eq. (7) $f(x)$ denotes the kernel function, which in the model acts on the original signal $h(k)$. Pooling is required to reduce the dimensionality of the signal. Where the overlap R between kernel size K and pool size P is:

$$R = \frac{K-1}{K+P-1} \quad (8)$$

The overlap rate R is significantly less than 1. If the dimensionality of the signal is reduced by using stride rather than pooling, the overlap rate needs to be kept around 0.5, but it was found that using stride performed worse than using pooling. When pooling is used, the most important information is extracted and useless information is discarded, however when using stride all information needs to be considered. In this case, it is necessary to keep $R < 0.5$, but it is not desired that it extracts consecutive frames. To create the model, consider $R < 0.5$ of all layers between the convolution and maximum pooling layers, i.e. $R \approx 0.4$.

3.3.4 Long and short-term memory neural networks

The core of LSTM is the cell state, which consists of forgetting gate, input gate and output gate, the structure of LSTM memory cell is shown in Fig. 4, because LSTM has a gating mechanism, the cell state can be changed by the passage of selective information. The relevant formula in its memory cell is shown in equation (9):

$$\begin{cases} f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \\ i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \\ \tilde{C}_t = \tanh\left(W_C\left[h_{t-1}, x_t\right] + b_C\right) \\ C_t = f_t C_{t-1} + i_t \tilde{C}_t \\ o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \\ h_t = o_t \tanh C_t \end{cases} \tag{9}$$

Where f_t denotes the forgetting gate threshold, f_t denotes the input threshold, $\tilde{C}_t$ denotes the cell state at the previous moment, and C_t denotes the cell state where the loop occurs. C_t denotes the output threshold, h_t denotes the output of the current cell, h_{t-1} denotes the output of the cell at the previous moment, b_f、b_i、b_C、b_o is the bias, and W_f、W_i、W_C、W_o is the connection weight.

4. AFFECTIVE COMPUTING MODEL CONSTRUCTION

In order to avoid having only a small number of labeled samples, it is not possible to train a classifier with high accuracy, which leads to low confidence in predicting the sentiment classification of unlabeled text. To address this situation, this paper will use three classifiers, Support Vector Machine, Plain Bayes, and Unsupervised Sentiment Dictionary-based Classifier, to classify and predict the text at the same time, integrating the results of the three classifiers for the final label determination. Let the confidence level of Artistic text d be

CS, and the confidence contribution values of SVM, Park Bayes, and Sentiment Dictionary-based classifiers to text d are defined as SCS, NCS, and QCS, respectively, then:

$$CS = K_1 * SCS + K_2 NCS + K_3 QCS \quad (10)$$

where K1, K2, and K3 denote the sentiment contribution weights of each subclassifier. When each classifier predicts the sentiment classification of artistry text and dance movements, the confidence contribution value of each classifier is set to 1 if the sentiment result is positive, and the confidence contribution value of each classifier is set to -1 if the sentiment result is negative, when the larger the value of CS, it means that the prediction opinion of each classifier is more unified, and the higher the confidence level is. Using self-training with semi-supervised learning, the samples with high confidence are added to the labeled sample set, and the loop iterates to reuse the new sample set to train the classifiers.

The sentiment contribution weight of each subclassifier refers to the degree of influence on the sentiment classification result. Different classifiers in the sentiment classification of text, in addition to the final results of the classifier, but also should take into account the classification ability of the classifier, classification ability of strong classifiers on the classification results of the degree of influence than the classification ability of the weak classifiers, rather than the same large, to address this situation, this paper introduces the individual subclassifiers of the emotional contribution of the weights. The strength of the classification ability is reflected in the classification accuracy of the classifier, for the same training text, the stronger the classifier classification ability, the higher its classification accuracy. So the values of the sentiment contribution weights K1, K2 and K3 of each subclassifier are equal to the classification accuracy of each subclassifier on the same test set.

5. ANALYSIS OF METAPHORICAL EXPRESSION IN THE TEACHING OF DESIGN AND DANCE IN ART STUDIES IN COLLEGES AND UNIVERSITIES

5.1 Data sets

The construction of the dataset in this paper is based on affective computing, and the following strategies are needed to support this goal:

(1) Establish the knowledge collection strategy and inclusion principles.

(2) Establish the principles and specifications of the linguistic annotation system and select the annotation set.

Using the Anaphora Annotated Corpus constructed in 2017, which is the largest known dataset for metaphorical interpretation ranking, in which the use of metaphorical sentences contains verbs, nouns, adjectives and complex words. Each data set of this corpus consists of five sentences, one metaphorical sentence and four explanatory sentences. The content of the metaphorical text covers happy, sad, sad and angry, and the sentiment analysis in this paper is for the study of metaphorical sentences, so the metaphorical sentences contained in the two corpora are screened, and each sentence is labeled with the aspect word and its corresponding sentiment polarity. After deleting the duplicate data, two datasets for metaphorical aspectual sentiment analysis are constructed respectively. The metaphoric aspect words are labeled as shown in Table 4, and the sentiment polarity is divided into three types: negative, neutral and positive, and different aspect or target words are labeled with their corresponding sentiment labels.

Table 4 Examples of metaphorical aspect words annotation

Metaphorical Sentence	Aspect 1	Affective Polarity 1	Aspect 2	Affective Polarity 2
A Crow Sang A Happy Song Ina Tree, and was Soon Drownedby Cicadas' Chattering.	Happy Song	1	Cicadas' chattering	-1

The difference between the number of positive labels, labels of 1 and the number of negative labels of -1 for each sentence is set to p. When $p>0$, the sentiment category of this sentence is positive sentiment, when $p<0$, the sentiment category of this sentence is negative sentiment, and when $p=0$, the sentiment category of this sentence is neutral sentiment. The dataset is shown in Table 5, and the dataset is divided into a training set and a test set in the ratio of 7:3. The test set is used to verify whether the emotion computation can accurately detect the emotion polarity of different dance movements.

Table 5 Data sets

		MPM-S	VUA-S
Positive	Training set	425	590
	Test set	183	253
Neutral	Training set	283	370
	Test set	123	160
Negative	Training set	380	514
	Test set	170	222

5.2 Sentiment analysis and evaluation

Using the constructed affective calculation model, the students' performance in the design and dance teaching of art studies was emotionally analyzed and evaluated to understand the students' affective state and affective changes, as well as their affective reactions to the teaching content. Forty-four 9-11-year-old dance beginners in the dance school were selected as experimental subjects and randomly divided into two groups, 21 in the control group and 23 in the experimental group. The experimental period was August-November 2023, a total of 16 weeks, every Saturday morning 10:00-11:30 for class time, a class time for 90 minutes, a total of 16 lessons. The experimental group had classes on Saturdays and the control group had classes on Sundays. The field equipment was teaching aids and sound. Pre-experimental test Before the first class of the experiment, the dance learning motivation test was administered to the students of the experimental group and the control group respectively, and before conducting the test, the tester first explained the test requirements to the subjects and demonstrated them. The post-test was administered in the last session of the experiment and at the end of the test, the experimental data were collected and saved to be analyzed with the pre-test scores. SPSS17.0 was used to do descriptive statistics, percentages, mean comparisons and other statistical and data processing of the data to provide data support and reality for this study and to provide a basis for quantitative analysis. Independent samples t-test was conducted on the scores of each dimension of motivation in the experimental and control groups before the experiment, and the results of learning motivation are shown in Table 6.

There were 21 learners in the control group and 23 learners in the experimental group. The table gives the mean $\bar{x}$ and standard deviation sd of each motivation dimension, as well as the t-value and p-value obtained by conducting the independent samples t-test. Based on the data in the table, it can be seen that in terms of fun motivation, ability motivation and appearance motivation, there is no significant difference between the scores of the control group and the experimental group ($p>0.05$), indicating that there is no significant difference between the two groups of trainees in terms of the initial level of these motivational dimensions. In terms of health motivation and social motivation, the difference between the scores of the control group and the experimental group is slightly close to the level of significance ($P<0.10$), indicating that there may be some degree of difference between the two groups of trainees in these two motivational dimensions, but it has not yet reached the level of significance.

Table 6 Dance learning motivation test

Group	Control Group (N=21)	Experimental Group (N=23)	T Palue	P Palue
Fun Motive	2.71±0.51	2.81±0.58	0.59	0.55
Competency Motivation	2.52±0.41	2.54±0.43	0.12	0.90
Health Motivation	3.43±0.52	3.31±0.45	-1.52	0.13
Social Motivation	2.78±0.45	3.01±0.48	1.67	0.10
Appearance Motive	2.96±0.55	3.12±0.48	0.85	0.39

5.3 Evaluation of the effectiveness of metaphorical expressions

This study measures the flow of emotional information by calculating college artistry and dance movements. Firstly, we calculate the information entropy of the original emotion word topic, that is, the degree of information confusion before the college teaching student. The three rounds of the experiment have increasing numbers of emotion words, 3 words, 4 words, and 5 words, and then have different response possibilities according to the different numbers of emotion words in each round, the first round contains 6 response possibilities, the second round contains 24 response possibilities, and the third round contains 120 response possibilities. These possible responses were regarded as equal probability events, so that the information entropy of the original emotion word questions in each round could be calculated. Next this study calculated the amount of information about each group of responding students in each round, i.e., the amount of information embodied in the results of the responses after the occurrence of college teaching. This was done by counting all the situations and the number of times each situation occurred for each group of students in each round, treating each situation as an event, comparing the number of times it occurred with the number of questionnaires to convert it into the probability of this event occurring, and then rooting out the amount of information about this event. Then the information quantity of the results of this round is obtained by summing up the information quantity of all events of each group in each round. The amount of information conveyed by the dance movement behavior is obtained by subtracting the information of the result from the original information entropy. Finally, this study counts the proportion of information delivered by each group in each round in its original information entropy, and this value can largely reflect the observer's perception of the degree of consistency. Figure 4 shows the transfer efficiency of emotion for each group, and seven of the 14 groups in the first round of experiments achieved an emotion transfer efficiency of 100. It should be noted that a 100% emotion transfer efficiency only means that all the group members of their group obtained a consistent emotion perception based on the line samples of their group, but whether or not there is any congruence between their perceived emotion and the emotion expressed by the drawer cannot be known from this, and needs to be judged in conjunction with the next subsection. It needs to be judged in relation to the correctness rate in the next subsection. There were five groups with poor emotion transfer efficiency, below 50%. In the end, the average emotion transfer efficiency of all groups in the first round is 76.24%, which is high. Of the 14 groups in the second round of the experiment, 3 groups had an emotion transfer efficiency of 100% and there were no groups with an emotion transfer efficiency of less than 50%. The average emotion transfer efficiency of all groups in the second round was 76.55%, which was slightly higher than the first round.Out of the 14 groups in the third round of the experiment, 4 groups achieved 100% efficiency in emotion transfer and there were no groups with less than 50% efficiency in emotion transfer. The average emotion transfer efficiency of all groups in the third round is 80.73%, which is an increase from the first and second rounds.

From the average affective transfer efficiency of the three rounds of the experiment, the overall average affective transfer efficiency of this pre-experiment was 77.84%. This somehow implies that when a certain drawer expresses a certain emotion by drawing a line, 77.84% of the observers can feel a similar emotion, which is obviously a high percentage. From this, it can be tentatively inferred that the dance movements based on this experimental framework have good performance in terms of the efficiency of emotional information transfer, and most of the observers are able to recognize consistent emotions from the emotional lines.In addition there is a special finding in this study which is different from the expectation, the average emotion transfer efficiency of the first, second and third rounds are 76.24%, 76.55% and 80.73% respectively, the emotion transfer efficiency does not decrease with the increase of emotion words, but rather shows a slightly higher trend. It would generally be assumed that when emotion words increase, the testers' responses may be more discrete and the emotion transfer efficiency decreases. However, this was not the case in the experimental results, which suggests that the causality of the testers' perception of the emotion of the dance movements may not be significantly reduced with the increase of emotion words.

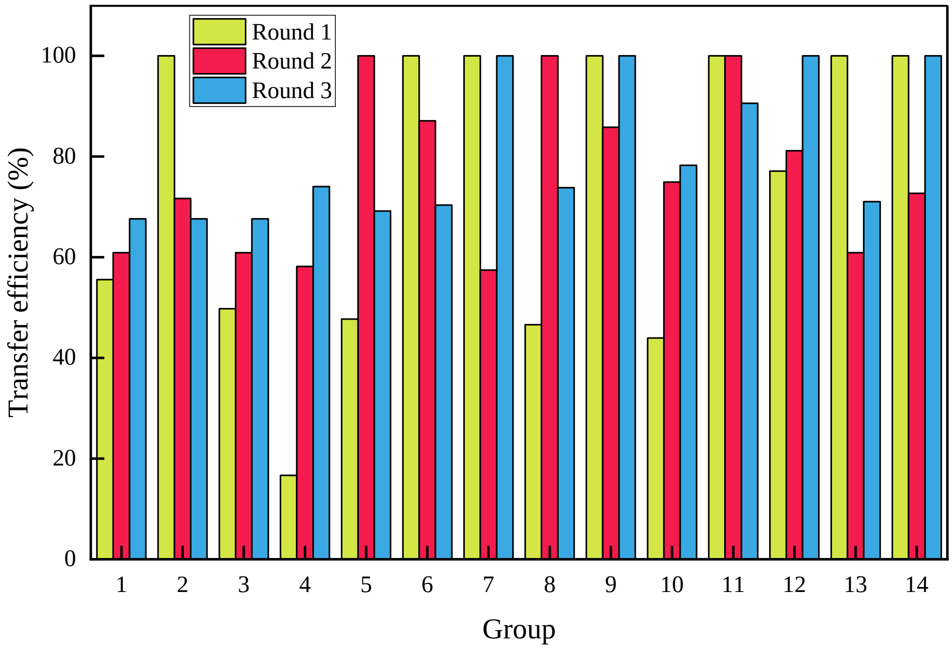

Figure 4 Emotion transmission efficiency of each group

6. CONCLUSION

The results analyzed by affective calculation in teaching artistry design and dance in higher education showed that there was no significant difference between the scores of the control group and the experimental group in terms of fun motivation, ability motivation, and appearance motivation > 0.05. This indicates that there was no significant difference between the two groups of learners in terms of their initial levels of these motivational dimensions. In addition, the results of the analysis in terms of affective transfer efficiency showed that in the first round of the experiment, 7 out of 14 groups had an affective transfer efficiency of 100%, indicating that the group members agreed on their affective perceptions of the line samples in their group. In the second round of the experiment, 3 out of 14 groups achieved 100% emotion transfer efficiency and no group had less than 50% emotion transfer efficiency. The average emotion transfer efficiency of all groups in the second round was 76.55%, which was a slight increase. And in the third round of the experiment, 4 out of 14 groups showed further improvement by reaching 100% emotion transfer efficiency. The study showed that the emotion transfer efficiency improved in different rounds of the experiment, showing a higher level. These results provide valuable references for future research on dance teaching and emotional expression, and may provide guidance for educational practice and curriculum design.

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