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Research Article

Emotional Analysis and Personalized Recommendation Analysis in Music Performance

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Music performance belongs to music recreation activities, is through singing, musical instrument performance, and vocal conductor, including a variety of artistic means, to convey music to the audience with real sound effects that can be felt, and can play its social function. Emotional state is a part of the whole attitude, which is consistent with introverted feelings and intentions in attitude, and is a complex and stable physiological evaluation and experience of attitude in physiology. This paper first introduces the concepts of music performance from the perspective of music appreciation and music ability. Then based on the emotional feature learning of matrix factorization constrained nonnegative matrix factorization and model optimization algorithm are used to analyze the emotional aspects of music. Finally, through the experimental comparison of the difficulty of emotion in various artistic creations, a conclusion is drawn. The research involves matrix decomposition, mathematical modeling, model optimization, digital audio technology application, and other fields. In the third part of this paper, the constrained nonnegative matrix factorization, the constrained nonnegative matrix factorization with external information, and the model optimization algorithm are used to study the mathematical modeling.

1. Introduction

In order to study the neural basis of spontaneous musical performance, we found the characteristics of improvisation by using two paradigms with great differences in musical complexity: extensive inactivation of dorsolateral prefrontal cortex and lateral orbital region, local activation of medial prefrontal cortex. This pattern may reflect the combination of psychological processes required for spontaneous improvisation, in which the change of prefrontal lobe activity is accompanied by extensive activation of neocortical sensorimotor area and inactivation of marginal structure [1]. This paper describes an expressive timing method that maps the pianist's musical thoughts to sound performance. In Experiment 1, the three modes of chord asynchronous, Rubato mode, and overlapping are all strong in the performance of experienced pianists, and each mode is weakened when pianists try to play nonmusic. In Experiment 2, the marked melody shows the most consistent amount of overlap between adjacent events [2]. Biofeedback-assisted regulation of cortical electrical activity has been shown to have intrinsic clinical benefits and has been shown to improve cognitive ability in healthy people. Related investigations have studied the music performance of students in Conservatory of Music under stress conditions [3]. The model of the performance principle of Rule K system is to choose the use rules and the amount of rules and then model the semantic description such as emotional expression. This paper discusses the communicative purpose and limitations of such rules at present and the future improvement [4]. In this paper, a new concept of speech synthesizer is proposed by constructing devices and methods capable of real-time operation. The further development of this concept may lead to the improvement of conversational ability of people with "verbal communicators" [5]. This paper analyzes the emotional state of movies based on emotional information and user experience and proposes movie browsing based on emotional information [6]. Social media has become a convenient platform for expressing opinions by posting messages, from texting to uploading media files or any combination of messages. Existing research on affective computing mainly focuses on a single media, whether it is text subtitles or visual content. In this paper, we discuss the learning of highly nonlinear relationships between low-level features under different modes of emotion prediction [7]. At present, MTV has become widely loved by people. Emotional analysis can extract emotional states included in MTV, which provides a potential and promising solution for efficient and intelligent access to MTV [8]. In this paper, information features are extracted from heterogeneous inputs to represent human emotions, and a hierarchical multimodal structure based on attention is proposed, which proves the visualization of this model and explains the attention to patterns [9]. Patients' emotional/emotional state is closely related to the rehabilitation process and their health. This paper presents the design and implementation of an emotion analysis module integrated in the existing telemedicine platform. The technical details of the implementation of the scheme are discussed, and the preliminary results of the accuracy and error of the scheme in actual operation are given [10]. With current position in film production, the distance from the camera to the subject greatly affects the narrative power of the lens. This paper investigates the use of shot distance in famous movie scenes, and the results show that the key factor to induce audience's emotional response is the pattern of shot type [11]. This paper describes a convenient method of editing and reproducing music performance data. Music performance data divided into a plurality of parts is edited, and an icon [12] is displayed at the original divided position in order to facilitate positioning the divided position of the block before changing the length. This paper mainly discusses the cognitive modeling of games and animation. Personalization represents a better way of communicating and doing business. Personalization is an opportunity that must be identified and designed to be useful and useable. Personalization has no single answer or solution, because it needs to be reviewed on a case-by-case basis [13]. In order to provide a more robust personalized context, we want to extract a continuum of users' general interests into specific interests, called the User Interest Hierarchy (UIH). A hierarchical clustering (DHC) algorithm is proposed, which does not need user participation, only needs to learn UIHS implicitly, and uses words and phrases to improve the quality of UIHS [14]. This paper introduces the key technologies related to personalization and studies the key technologies of personalization in detail by comparing with the existing prototype system. In addition, three representative personalization systems are analyzed [15].

2. Musical Performance

2.1. Music. Music, as an independent art category, is the most familiar and favorite artistic expression form in people's daily life. However, if specific concepts are mentioned, there will be various discussions. One is the art of expressing people's thoughts and feelings and reflecting real life with organized music. Another expression is that music is an art created by human beings, which exists by means of sound wave vibration, is displayed in time, and causes various emotional reactions and emotional experiences through human auditory organs. Compared with the definitions of the above three entries, Modern Chinese Dictionary gives a more general explanation, only emphasizing "organized music". If this part is replaced by the expression of art, this definition can also become a general formula to express another kind of art.

2.2. Music Appreciation. Music appreciation, as an independent process of music creation, is an important field that music aesthetics and music psychology have been paying attention to. Music appreciation refers to a kind of aesthetic activity that takes specific music works as the object and understands the true meaning of music by listening and other auxiliary means, such as reading and analyzing music scores and related background materials, so as to get spiritual pleasure.

2.3. Capabilities. The definition of "ability" in Modern Chinese Dictionary is "the ability, strength, or condition to be competent for a certain job or do a good job." According to the functional classification of ability, it can be divided into three types: cognitive ability, operational ability, and social ability. Cognitive ability includes learning, research, understanding, general situation, and analysis ability; operational ability includes the ability to manipulate, make, and move; social ability is the language expression ability in social communication activities. By comprehensive comparison, the first definition is more convincing.

2.4. Music Appreciation Ability. Music appreciation ability can be understood as the level of music skills and music understanding achieved when individuals participate in music appreciation activities, and appreciation mainly includes auditory ability and music reading ability. By studying six basic concepts: music performance specialty, music, music appreciation, ability, music ability, and music appreciation ability, music appreciation in the curriculum system of music performance specialty, we have a clearer theoretical understanding of music and music education from four aspects: art category, discipline and specialty, music creation, and music ability. These concepts are the theoretical support and principle foundation for engaging in music practice activities and also lay an important foundation for the next research on the framework of music appreciation ability.

3. Emotional Feature Learning Based on Matrix Factorization

3.1. Constrained Nonnegative Matrix Factorization. Nonnegative matrix factorization appears to deal with the problem that the dimension of input data is too high in the real world. After the original data is represented as a matrix, we can find two nonnegative matrices by NMF technology, and their products can approximate the original matrix well, thus mapping the features of the two dimensions to a hidden space at the same time. Based on the emotional representation in music field, NMF technology is explained in detail. The main issues in this section are translated into constructing a song list-song matrix, using NMF to map songs and songs to emotional space at the same time, and obtaining the representation or distribution of song list and songs in emotional space. The corresponding data expression form is as follows: song list-song representation: the cooccurrence information of song list and song is represented as a two-dimensional matrix, in which each row represents a song list and each column represents a song. The value in the matrix is 0 or 1, which indicates whether the corresponding song appears in the song list (1 appears, 0 does not appear). Because of the huge number of songs in the song list, in the data calculation, there will be some problems, such as excessive resource consumption and long time consumption, and the excessive frequency of some songs will interfere with the decomposition effect. Therefore, it is necessary to preprocess the original song list data, select some songs as the features of the song list, and then obtain the original matrix X through matrix representation. Suppose that the size of matrix X is M rows and N columns, M represents the singular number of songs, and N represents the number of songs. The form of matrix X is

$$\begin{pmatrix} a_{11}\cdots a_{1n} \\ \vdots \\ a_{m1}\cdots a_{mn} \end{pmatrix}. \tag{1}$$

Matrix factorization objective: NMF aims to find the nonnegative factorization matrix of two original matrices X to replace U and V and make X close to the factorized result UVT, that is, minimize the following objective function, and obtain formula

$$\begin{gathered} o = \left\| X - UV^T \right\|_F^2 \\ s.tU \geq 0, V \geq 0. \end{gathered} \tag{2}$$

Among them, $\| \cdot \|_F^2$ represents the Frobenius norm of the matrix, and the constraint condition is that the weight distribution value of the decomposed U and V matrices in the emotional dimension is greater than or equal to 0; that is, negative values cannot appear.

Under the problem of emotional representation of music, the original song list matrix is decomposed into song list-emotion matrix U and song emotion matrix V by NMF. Because there is no orthogonal restriction, the final result is the distribution representation of song list and song in emotional space.

3.2. Constrained Nonnegative Matrix Factorization with External Information

3.2.1. Emotional Tag Information. In the context of emotional representation of music, expert labeled song list or emotional label information at song level is introduced as external information to be included in matrix decomposition. The following takes the song label information Vo marked by the annotator expert as an example to discuss the relevant formulas. The annotator of Uo is similar to Vo; just replace the corresponding V with U.

Let the song emotion label matrix marked by some experts be V_0, each row corresponds to the song list of the original matrix X, and each column corresponds to emotion. The value in the matrix is 0 or 1. If the song list has an emotion label, the corresponding value is 1; otherwise it is 0. On the basis of the original matrix decomposition objective, the error between the decomposed matrix V and the prior information matrix V_0 should be as small as possible; that is, the objective function is minimized as formula

$$\left\| G_V \left(V - V_0 \right)_0 \right\|_F^2, \tag{3}$$

where G_V is the diagonal indication matrix representing the song level, $G_V(i,i) = 1$ indicates that the i-th song contains emotional indication, and $G_V(i,i) = 0$ does not.

If the emotion representation learned by matrix factorization is inconsistent with the emotion indication contained in the data, this loss function will generate penalty, thus optimizing the direction of the next decomposition in matrix factorization.

3.2.2. B Networks. This kind of external information reflects the correlation between nodes. Similar songs or song lists are more likely to contain similar emotions, and the relationship between nodes is represented by constructing a graph network. In a graph, each node represents a data point, and the edges between nodes represent the correlation between data points. The adjacency matrix of a graph can be defined as formula

$$W^u(i,j) = \begin{cases} 1, & \text{if } u_i \in N(u_i) \text{ or } u_j \in N(u_i), \\ 0, & \text{otherwise}. \end{cases} \tag{4}$$

Among them, u_i is a song in the song list, and $N(u_j)$ represents K nearest residences of song J. Neighbors here can be obtained by many metrics, and the adjacency matrix is further constructed. The loss function of the song list relationship network can be defined as formula

$$R_u = \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \left\| U(i,^*) - U(J,^*) \right\|_2^2 W_u(i,j). \tag{5}$$

It can be reduced to formula

$$R_u = Tr\left(U^T L^u U\right), \tag{6}$$

where $Tr(\cdot)$ is the trace of a matrix, which is a Laplace matrix, D^u is a diagonal matrix, and $D^u(i,i) = \sum_{j=1}^{m} W^u(i,j)$. R represents the loss function of the song list relationship network. If two songs are close in the graph but have different emotional labels, this loss function will produce penalty; that is, in the process of matrix factorization training, this loss function will tend to give similar emotional labels to songs close in the graph. The definition of the relationship network of song dimension is similar to that of song list; only the corresponding U needs to be replaced with V.

In the real world environment, there are many kinds of data that can be used to measure the distance relationship between song lists. This paper mainly constructs the relationship network from the perspective of song lists, including two kinds of external information: cooccurrence based on text label features and cooccurrence based on songs in song lists. These two kinds of external information and their respective validity will be explained in detail in the following steps.

Based on the feature similarity of text tags, each song list is mapped to the text feature space formed by tags as feature words and represented in the form of vectors. The neighbors of each song list are determined by calculating the similarity between vectors. The higher the similarity, the closer the two songs. The calculation process is as shown in formula

$$\mathrm{sim}(i,j)=\frac{v_i\cdot v_j}{\|v_i\|\|v_j\|}, \tag{7}$$

$\mathrm{sim}(i,j)$ represents the similarity between song list i and song list j, and v_i and v_j represent the vectorial representation of song list i and song list j in feature space, respectively.

Based on song cooccurrence: One song list contains multiple songs at the same time, and the same song may also be included in multiple songs.

Finally, the objective function incorporating external information can be expressed as formula

$$\begin{cases}\min & J=\|X-UV^T\|_F^2+\lambda_I^u\|G^u(U-U_0)\|_F^2+\lambda_I^v\|G^v(V-V_0)\|_F^2+\lambda_c^u Tr\left(U^TL^uU\right)+\lambda_c^u TrV^TL^vV,\\ s.t & U\geq 0, V\geq 0.\end{cases} \tag{8}$$

$\lambda_I^u,\lambda_I^v,\lambda_c^u,\lambda_c^v$ are the coefficient in front of the song list-emotion label information item, the song emotion label information item, the song list relationship network item, and the song relationship network item. It represents the weight of each item in the objective function. The greater the weight, the higher the proportion of corresponding items, and the training direction will tilt towards the direction of fitting the item, that is, the greater the weight of discourse power, the higher the proportion of corresponding items, and the training direction will tilt towards the direction of fitting the item, that is, the "discourse power" is greater. Because of the practical significance of the data, there cannot be negative numbers in matrices U and V.

From the data point of view, the original matrix decomposition revolves around the representation of songs in song lists or song lists on songs and incorporates the matrix decomposition of external information. On the basis of the original information, the information such as the correlation between songs and songs, the correlation between song lists and song lists is supplemented, which makes up for the defect of insufficient original data.

3.3. Model Optimization Algorithm

3.3.1. A Calculation of Matrix U. The problem of calculating Matrix U is equivalent to solving the following optimization problem, such as formula

$$\begin{cases}\min & J=\|X-UV^T\|_F^2+\lambda_I^u\|G^u(U-U_0)\|_F^2\\ & +\lambda_c^u Tr\left(U^TL^uU\right),\\ s.t & U\geq 0.\end{cases} \tag{9}$$

Let Λ_U represent the Lagrange multiplier corresponding to the constraint condition $U\geq 0$; then the Lagrange equation can be defined as formula

$$\begin{aligned}L(U)=&\|X-UV^T\|_F^2+\lambda_I^u\|G^u(U-U_0)\|_F^2\\&+\lambda_c^u Tr\left(U^TL^uU\right)-Tr\left(\Lambda_U U^T\right).\end{aligned} \tag{10}$$

Let $\nabla_U L(U)=0$ give formula

$$\begin{aligned}\Lambda_U=&-2XV+2UV^TV+2\lambda_I^uG^u(U-U_0)\\&+2\lambda_c^u(D^u-W^u)U.\end{aligned} \tag{11}$$

According to the KKT complete condition, formula (12) can be obtained:

$$\Lambda_U(i,j)U(i,j)=0. \tag{12}$$

KKT complete condition is a method used to solve optimization problems.

Thus, formula (13) can be obtained:

$$\begin{aligned}&\left[-\left(XV+\lambda_I^uG^uU_0+\lambda_c^uW^uU+\left(UV^TV+\lambda_I^uG^uU+\lambda_c^uD^uU\right)\right]\right.\\&\cdot(i,j)U(i,j)=0.\end{aligned} \tag{13}$$

The iterative rule of Matrix U is formula

$$U(i,j)\leftarrow U(i,j)\sqrt{\frac{\left[XV+\lambda_I^uG^uU_0+\lambda_c^uW^uU\right](i,j)}{\left[UV^TV+\lambda_I^uG^uU+\lambda_c^uD^uU\right](i,j)}}. \tag{14}$$

3.3.2. B Calculation of Matrix V. The problem of calculating Matrix V is equivalent to solving the following optimization problem, such as formula

$$\begin{aligned}\min J=&\|X-UV^T\|_F^2+\lambda_I^v\|G^v(V-V_0)\|_F^2\\&+\lambda_c^v Tr\left(V^TL^vV\right)-Tr\left(\Lambda_V V^T\right).\end{aligned} \tag{15}$$

Let Λ_V represent the Lagrange multiplier corresponding to the constraint condition $V\geq 0$; then the Lagrange equation is defined as formula

$$\begin{aligned}L(V)=&\|X-UV^T\|_F^2+\lambda_I^v\|G^v(V-V_0)\|_F^2+\lambda_c^v Tr\left(V^TL^vV\right)\\&-Tr\left(\Lambda_V V^T\right).\end{aligned} \tag{16}$$

Let $\nabla_V L(V) = 0$ give formula (11):

$$\Lambda_U = -2X^T U + 2VU^T U + 2\lambda_I^v G^v (V - V_0) + 2\lambda_c^v (D^v - W^v) V. \tag{17}$$

According to the KKT complete condition, formula (18) can be obtained:

$$\Lambda_V (i, j) U (i, j) = 0. \tag{18}$$

Thus, formula (19) can be obtained:

$$\left[-\left(X^T U + \lambda_I^v G^v V_0 + \lambda_c^v W^v V \right) + \left(VU^T U + \lambda_I^v G^v V + \lambda_c^v D^v V \right) \right] (i, j) V (i, j) = 0. \tag{19}$$

The iterative rule of Matrix V is formula

$$V (i, j) \leftarrow V (i, j) \sqrt{\frac{\left[X^T U + \lambda_I^v G^v V_0 + \lambda_c^v W^v V \right] (i, j)}{\left[VU^T U + \lambda_I^v G^v V + \lambda_c^v D^v V (i, j) \right.}}. \tag{20}$$

3.4. Music Emotional Representation Learning. The essence of music emotion recognition is the representation of music or songs in emotion space. By using the nonnegative matrix factorization algorithm which fuses external information, we can get song list-emotion matrix U and song emotion matrix V. Matrix V is the representation or distribution of each song in emotion space. In order to obtain more practical results, each row of matrix V is normalized, and each row corresponds to the probability distribution of a song in emotional space. Let the emotional distribution of the first song I be V_i ; then the song I is expressed as formula (21) in k-dimensional emotional space:

$$V_i = (V_{i1}, V_{i2}, \ldots, V_{ik}). \tag{21}$$

By normalizing V_i corresponding to the first song I, the emotional probability distribution s_i^* corresponding to the song I can be obtained, and the calculation is as formula

$$s_i^* = \left(\frac{V_{ij}}{\sum_{j=1}^{k} V_{ij}} \right). \tag{22}$$

K represents the emotional space dimension.

For each song, the emotion class with the highest corresponding value is taken as the emotion class to which the song belongs, and the calculation is as formula

$$e_i^* \leftarrow \arg\max (s_i^*). \tag{23}$$

Therefore, the purpose of song emotion recognition is achieved.

The above algorithm is the complete process of music emotion recognition algorithm based on matrix decomposition. Based on the matrix decomposition method, we can achieve the purpose of emotional representation of songs in the song list. After obtaining the representation of songs in emotional space, we can carry out the work of emotional recognition for users.

4. Analysis of Important Indexes in Music Performance Major

4.1. Analysis of Teaching Results. We evaluate the teaching achievements through three directions: skill assessment, ability growth assessment, and objective analysis of digital audio technology. In order to better understand the situation of students' training and skills mastery, all students' training audio records will be collected every week as a reference for ability evaluation. Audio recordings of live performances will be used as data sources for digital audio technology analysis.

The assessment steps are as follows:

(a) Students are assessed for on-site skills display in groups, and the assessment place is the Concert Hall of the College. Seven music performance teachers are invited to score the students' on-site skills assessment one by one.

(b) The assessment place is the digital audio training room, where teachers score students' growth ability according to the staged training audio stored before. On-site skill display score and growth ability score are calculated according to the perfect score of 100.

(c) The examination place is the digital audio training room, where teachers open the audio files of students' examinations and, through the visual analysis of digital audio technology, count the error rates of students' important and difficult points (there are 15 important and difficult points in total).

(d) The scores of the numeric group are compared horizontally with those of the traditional group, and then the scores are compared vertically within the numeric group and the traditional group.

4.2. Analysis of Data Results. Through the data analysis in Table 1, it can be found that the overall scores of students in the three sections remain stable, and the grades of "excellent", "good," and "poor" have not changed. It shows that the application of digital audio technology in teaching and practice in a short period of time has not significantly improved the teaching achievements. Although students with good foundation have not been assisted by digital audio technology, they can still achieve good results through traditional teaching mode and their own efforts, so that their professional level can be stably maintained at a certain level. However, through the comparison between the digital group and the traditional group, it is found that the scores of the digital group are slightly higher than those of the traditional group in the same level, and the average score of the digital group is 1.9 points higher than that of the traditional group. The average score of the digital group is 7.2 points higher than that of the traditional group. The average score of the number three group is 5.4 points higher than that of the traditional three groups. The data show that the number group in the skill display assessment has achieved certain advantages compared with the traditional group, and its final scores are slightly higher than each other.

Table 1: Statistical table of on-site skill display and assessment of music performance major.

Group	Number of people	Error rate	Rank
Number 1 group	10	92.5	1
Number 2 group	10	88.7	3
Number 3 group	10	75.2	5
Traditional 1 groups	10	90.6	2
Traditional 2 groups	10	91.6	4
Traditional 3 groups	10	92.6	6

Table 2: Statistical table of operational ability examination of music performance specialty.

Group	Number of people	Average score	Rank
Number 1 group	10	83.6	2
Number 2 group	10	91.4	1
Number 3 group	10	81.7	3
Traditional 1 groups	10	80.4	4
Traditional 2 groups	10	79.3	5
Traditional 3 groups	10	75.5	6

Through the data analysis in Table 2, we can find that the ranking of growth ability breaks the original balance, and the digital group is higher than the traditional group in terms of ability growth. Compared with the traditional one, the average score of the number one group is 3.2 points higher; compared with the traditional two groups, the average score of digital two groups is 12.1 points higher; compared with the traditional three groups, the average score of digital three groups is 6.2 points higher. It can be seen that, through the application of digital audio technology, the professional and technical level of students in the digital group has grown to a certain extent, and the degree of improvement in business ability is higher than that in the traditional group. Through the comparison within the group, it is found that the number two group gets the highest score of 91.4, which shows that the students with medium professional scores have the greatest ability improvement under the application of digital audio technology. Through the comparison of the growth ability value, it is found that the digital sound forehead technology has achieved certain results in the practical training and self-improvement in the teaching process.

Through Table 3, the ranking of the error rate of important and difficult points evaluated objectively is found to be completely consistent with the ranking in Table 1, which shows that students with good foundation have good performance under the traditional teaching mode. Compared with the students in the traditional group, the level of control error rate in the digital group is slightly higher. The error rate in Table 3 refers to the error frequency of the students surveyed in the performance assessment of music performance major. Compared with the traditional group, the error rate of the digital group is 3% lower; compared with the traditional two groups, the error rate of the digital two groups is 8% lower; compared with the traditional three groups, the error rate of the digital three groups is 5% lower. It can be seen that, through the application of digital audio technology, the professional and technical level of students in the digital group has grown to a certain extent, and the degree of improvement in business ability is higher than that in the traditional group. On the other hand, the number group has a slightly better control over the details of the performance. There is a big difference between performing in the sound field of the concert hall and the usual training environment. Students who create analog sound field training through digital audio technology are familiar with the sound feedback of the sound field of the concert hall, so the students in the digital group play more stably and well in the same environment. It can be seen that the practical training of digital audio technology application is helpful for students to improve the accumulation of performance experience and grasp the performance details.

Table 3: Statistical table of error rate of important and difficult points in performance examination of music performance major.

Group	Number of people	Error rate	Rank
Number 1 group	10	9	1
Number 2 group	10	13	3
Number 3 group	10	27	5
Traditional 1 groups	10	12	2
Traditional 2 groups	10	21	4
Traditional 3 groups	10	32	6

Integrate the data of the three score tables, and get the comparison diagram of the assessment results of instructional design as shown in Figure 1.

By analyzing Figure 1, it is found that the students who apply digital audio technology in teaching have significantly improved their skills, learning accuracy, and error rate control in a short time. Under the traditional teaching mode, students' skills, learning accuracy, and error rate control have also been improved, but compared with the number group, they are slightly inferior.

In order to better analyze the influence of the teaching mode on the teaching results, the teacher also scores the training situation of the target tracks recorded by the students at each stage after each professional class according to the technical level displayed by the students in the training and selects the final assessment score for the fourth time. After the scores are integrated by groups, the average value is calculated, and the data analysis is carried out to obtain the staged evaluation comparison chart as shown in Figure 2.

In Figure 2, the staged evaluation and comparison data of each group show that the application of digital audio technology has advantages and disadvantages, but its disadvantage is that it cannot improve the error rate. According to the analysis of Figure 2, with the teaching progress and the increase of teaching time using digital audio technology, the students' achievements in skill display have increased correspondingly and exceeded the teaching achievements obtained under the traditional mode. It shows that the application of digital audio technology can prove the promotion of students' skills. The ordinate in Figure 2 represents the average value of the scores obtained after the students' technical level is uniformly scored according to the group.

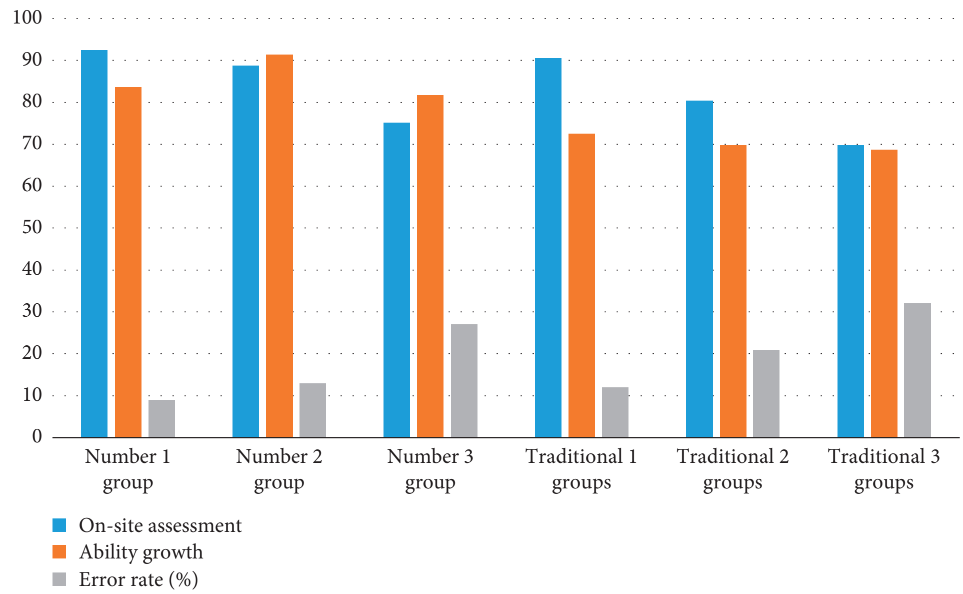

Figure 1: Comparison of assessment results.

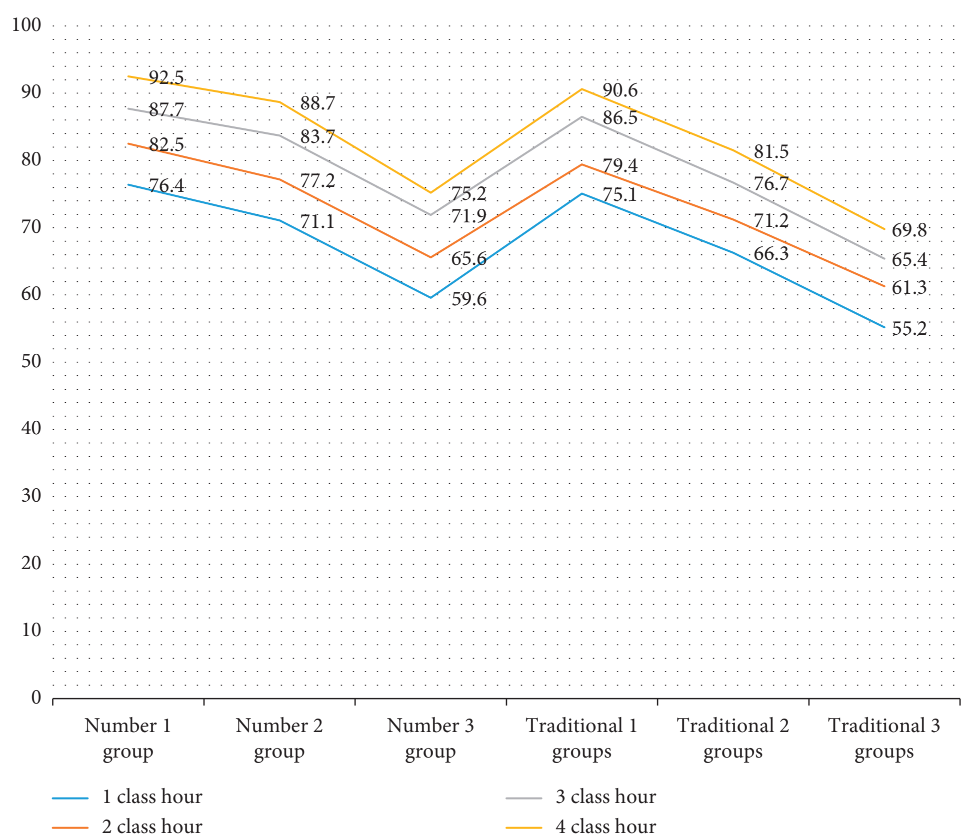

Figure 2: Comparison chart of staged evaluation.

4.3. Comparison of Emotional Experience in Music Performance

4.3.1. There Are Two Kinds of Human Emotions. One is called self-emotion, which is the emotional experience felt from life; the second is the emotional experience felt from art, which is also called the second self-emotion. Of course, the emotion in artistic creation refers to the second emotion, that is, aesthetic emotion. The above two kinds of emotions are dynamic psychological factors. The joys and sorrows we often say are not emotions in psychology, but a product between subject and object.

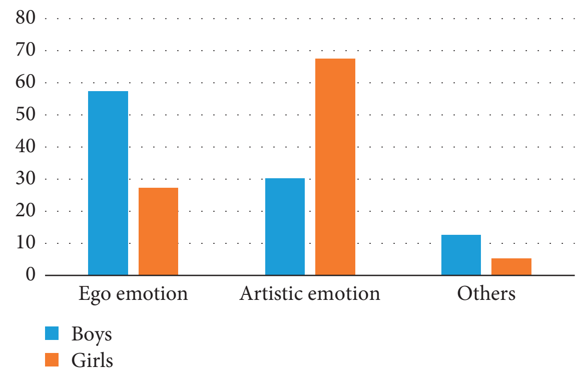

FIGURE 3: Comparison of the proportion of boys and girls who have emotions in music performances.

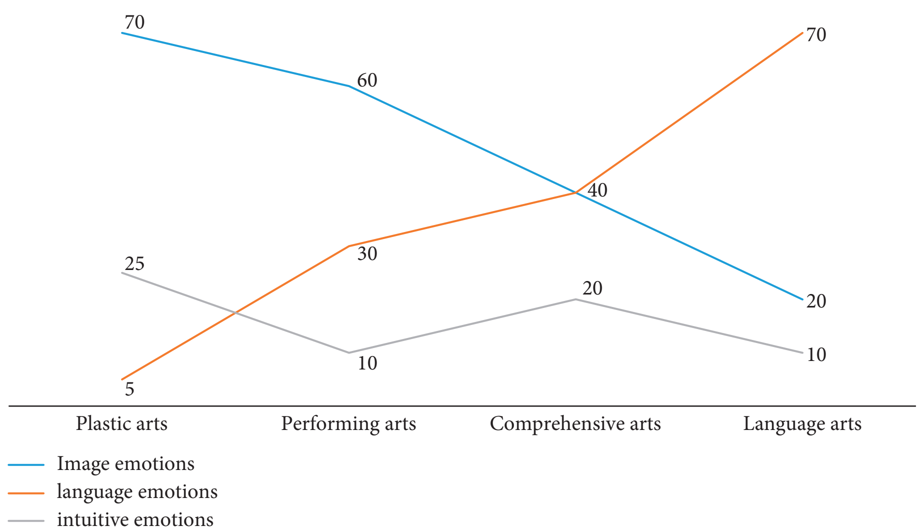

FIGURE 4: Difficulty of producing three emotions in various artistic creations (%).

According to the analysis of Figure 3, girls are more artistic than boys in music performance, and they are more likely to produce artistic emotion.

4.3.2. In the Process of Creating Art, There Are Usually Three Emotions. The first is the emotion that can be expressed by image, the second is the emotion that can be expressed by language, and the third is the intuitive emotion, which cannot be expressed by language or vision. When singers face creators' works, if they do not rely on their own emotions, they cannot understand the emotions in their works, and if they do not understand them, they will not resonate naturally.

By analyzing Figure 4, sound can effectively stimulate people's emotional fluctuations, which has a great stimulating effect on people. Music shows life through sound, and music reflects people's psychology through thoughts and feelings, which is also the difference between music and other arts. According to the analysis of Figure 4, art can be divided into four categories: plastic arts, performing arts, comprehensive arts, and language arts. In the process of artistic creation, plastic arts are most likely to produce image emotion, while language arts are most likely to produce language emotion. Performing arts and comprehensive arts are quite difficult.

5. Conclusion

By comparing the matrix algorithm with the experiment, it is an important content to study the emotional state in the process of music performance, because music performance is a comprehensive and challenging art form, which has a great relationship with the emotional state of singers, so the premise of successful music performance is to have good psychological quality and singing emotion. If you want to have good psychology, you should strengthen psychological training, accumulate performance experience constantly, cultivate your own psychological mobilization ability, and master psychological connotation deeply. Only by doing our best to improve ourselves can we better grasp the psychological state during performance. In the era of information explosion, personalized recommendation greatly solves the problem of information overload. By designing corresponding algorithms to capture users' personalized preferences and recommend items that users may like, it greatly reduces the difficulty of users' choice and increases the income of service providers. Personalized recommendation is one of the most practical and academic fields in the era of artificial intelligence. In recent years, especially in the last three years, we have witnessed the development of recommendation system, especially with the rise of machine learning and deep learning, the development of recommendation system is more rapid, and now it has expanded many subdivisions. The two models proposed in this paper mainly focus on KG and then combine graph representation learning technology to realize personalized recommendation. Through reading a large amount of latest research, this paper designs a novel graph representation learning algorithm to learn the feature representation of users and items. Experiments show that the model proposed in this paper has achieved good results, but there are still many areas to be improved, and there are still many challenges and research gaps in the future.

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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