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A Study of the Impact of the Integration of Technology and Composition on the Future Development of the Music Discipline

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SUMMARY: *The article builds a music intelligent creation model by utilizing transform framework, and preprocesses music data through data embedding and location information encoding operations, deeply integrating technology and music creation. Combined with the encoder and decoder equipped with various attention mechanisms, the music intelligent creation is gradually realized through the steps of weight matrix calculation and linear transformation projection. In order to clarify the impact of the model on the future development of the music discipline, the model is applied in a music academy using classroom multimedia equipment as a medium. The results of the study are as follows: the music intelligent creation model enhances the feedback atmosphere of the traditional music classroom, and the average score of the students in each index is more than 3.9 points. The average scores of students' aesthetic perception ability, artistic expression ability, cultural comprehension ability, and creative practice ability in the post-test were within the range of 3.88-4.52, which were 0.84-1.24 points higher than the scores in the pre-test. In addition, students' average theory scores and music skill levels improved to 84.10 and 81.78 points, respectively. The results of the regression model showed that the classroom feedback atmosphere, music core literacy, and music theory and skills had highly significant positive effects on the future development of music discipline.*

KEYWORDS: *transform framework; data embedding; attention mechanism; music composition model; music discipline development*

1 Introduction

Since Edison's invention of the phonograph at the end of the 19th century, the influence of science and technology on music creation and development has gone through three stages of analog technology, digital technology and intelligent technology, starting with the recording and playing of music through mechanical vibration, and ending with the introduction of electronic musical instruments, the rise of tape recording technology, the popularization of digital audio workstations and MIDI technology, and the emergence of intelligent music creation aids, the influence of science and technology on music has been in evolving [1-3]. Developing to today, deep learning models are widely used in the field of music generation [4]. Artificial Intelligence (AI) can not only generate music, but also carry out music style recognition, music analysis and other work, intelligent music creation has become an important development direction of the music industry [5].

Technology is a tool, and emotion is the kernel [6]. Regardless of how technology advances, the essence of music is still rooted in human emotional experience and cultural accumulation

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[7]. Human intelligence contains caring, concern, sympathy, love, curiosity, and the richness of emotions of joy, anger and sadness, and the creation of an excellent musical work comes from the musician's life experiences, joys and sufferings [8]. No matter how technology develops, music is always the carrier and extension of human emotions. From Ah Bing with a “two springs reflecting the moon” will be the inner suffering and struggle to pour out, to modern musicians with AI intelligent assisted creation, the core of the music has not changed, is still through the melody, rhythm and harmony, to express the musician's perception of life, the world, their own emotional experience and understanding of the audience [9, 10]. It can be said that technology is changing, but the essence of music has not changed.

At the same time, technology expands the boundaries of creation [11], AI technology provides infinite possibilities for creation, musicians should make good use of the tools, focusing on creativity and emotional expression, to realize the symbiotic relationship of “music as the basis, technology as the use” [12, 13]. The progress of technology has reduced the difficulty of music creation, expanded the infinite space of timbre and range, and improved the efficiency of creation [14]. Especially with the explosive development of AI technology, intelligent music creation has become a thing that everyone can do, and provides unlimited possibilities for musicians' professional creation [15]. Through the AI intelligent platform can complete the lyrics creation, style selection, arranging and orchestrating, synthesizing and outputting, video creation and other full-process style music production [16]. As musicians, they should actively embrace and use intelligent technology, and devote more time and energy to emotional and creative expression.

In recent years, the application of AI in music creation has become more and more prominent, from simple music generation software to complex intelligent composition system, and its changes to the way of music creation cannot be ignored. At the same time, human-computer collaboration, as an emerging mode of creation, is gradually becoming a research hotspot in the field of music creation [17]. On the one hand, with the increasingly diversified and personalized demand for music works, the traditional music creation method has been difficult to meet the rapidly changing market demand [18]. The emergence of AI technology has brought new possibilities for music creation, such as the ability to quickly generate a large number of music materials, simulate various music styles, etc., which allows creators to break through the limitations of traditional creation with the power of AI, improve the efficiency and quality of creation, so as to better adapt to the market demand [19-21]. On the other hand, from the perspective of academic research, the application of human-computer collaboration mode in music creation involves the cross-fertilization of multiple disciplinary fields, including musicology, computer science, psychology, aesthetics, etc., which provides rich research materials and broad research space for interdisciplinary research, and helps to promote the development and improvement of theories of related disciplines [22]. Therefore, it is of great practical significance and academic value to choose the topic of “Research on the Impact of the Integration of Science and Technology and Creative Writing on the Future Development of Music Disciplines”.

The study uses the TRANSFORM model to realize the integration of technology and music creation through music data embedding and location information encoding. The model uses the self-attention mechanism and Softmax function to get the normalized note weight matrix, realizes the multi-dimensional segmentation of the note data through the multi-head attention mechanism, and then the feed-forward propagation layer transforms the input signals in a non-linear way in order to improve the model training speed and expressive ability. The music composition performance of the model is evaluated by the overall effect of music composition as well as the note characteristics, and then the trained model is applied to colleges and universities to further analyze the impact of the model on the future development of the music discipline through the evaluation of classroom feedback, music core literacy, and so on.

2 Music intelligent creation model construction based on transform framework

In order to realize the deep integration of technology and music creation, the study designs a music intelligent creation model based on the TRANSFORM framework and applies it to music teaching practice, which provides technical support for the following study of the integration of technology and creation on the future development of the music discipline.

2.1 Music data preprocessing

2.1.1 Data embedding

The study used the REMI algorithm developed by the Google Brain team to convert the music into a matrix to obtain $X \in \mathbb{R}^{n \times N}$, where n is the number of elements contained in the song (which includes chords, notes, rests, bar numbers, etc.) and N is the dimension into which a musical notation is represented. Next, a three-dimensional array can be obtained by combining m music songs together. Then, through data embedding operations, each element of this piece of music is projected in ascending dimensions, and in general the higher the dimensionality of the projection, the more dimensions can be learned. The way of unfolding is:

$$X_1 = X * W_E W_E \in \mathbb{R}^{N \times D_{model}}, X_1 \in \mathbb{R}^{n \times D_{model}} \tag{1}$$

2.1.2 Encoding of location information

After data embedding, it is necessary to add the positional information encoding, the positional information encoding used in the study is the positional encoding of the sine cosine used in the transform model. For the score $X_{[1]}\left(X_{[1]} \in n * D_{model}\right)$ for which the word embedding is computed, for its n th row, the elements of the i th column are computed as follows:

$$X_{[1]n,i} = \begin{cases} X_{[1]n,i} + \cos\left(n / 10000^{2i/D_{model}}\right), i \bmod 2 = 0 \\ X_{[1]n,2i+1} + \sin\left(n / 10000^{2i/D_{model}}\right), i \bmod 2 = 1 \end{cases} \tag{2}$$

2.2 Encoders and Decoders

The encoder and decoder are each composed of a different structure, they are mostly the same process, slightly different in some detail processing.

2.2.1 Self-attention mechanisms

The transform model proposes a self-attention mechanism that allows each note to compute weights in parallel with other notes without relying on the output of its presequence sequence, and without the problem of excessive memory usage due to the need to store note elements that are too far away.

To compute the weights, we need a set of K (Key) and V (Value), and also a Q (Query). This is calculated by randomly initializing three matrices and multiplying them with $X_{[1]}$, which gives us the Q, K, and V matrices:

$$Q = X_{[1]} * W_q, W_q \in \mathbb{R}^{D_{model} * D_{model}} \tag{3}$$

$$K = X_{[1]} * W_k, W_k \in \mathbb{R}^{D_{model} * D_{model}} \tag{4}$$

$$V = X_{[1]} * W_v, W_v \in \mathbb{R}^{D_{model} * D_{model}} \tag{5}$$

where $Q, K, V \in \mathbb{R}^{n * D_{model}}$, after obtaining Q, K, V matrix, that is, you can use the current note to calculate the weights of all the other notes, and after obtaining the weights, multiply them with V, which means that you can get the weights A, and the weights A is calculated as:

$$A = \frac{Q * K^T}{\sqrt{D_{model}}} \tag{6}$$

After obtaining the weights $A\left(A \in \mathbb{R}^{n \times n}\right)$, it is necessary to normalize them using the Softmax function with the formula as:

$$A_{i,j}^{[1]} = \frac{e^{A_{i,j}}}{\sum_{j=0}^{D_{model}} e^{A_{i,j}}} \tag{7}$$

$A^{[1]}$ is the weight matrix, which represents the weights obtained by calculating the similarity between the current note and other notes. Once the weights are obtained, they need to be multiplied with the V matrix to obtain the final weights calculation result matrix $A^{[2]}$:

$$A^{[2]} = A^{[1]} * V \tag{8}$$

At this point, the self-attention mechanism has been calculated.

After obtaining the weight calculation result matrix $A^{[2]}$, it needs to be merged into the $X_{[1]}$ matrix, i.e., the weight information is merged with the input information. The merging is done by summing, i.e.:

$$X_{[2]} = X_{[1]} + A^{[2]}, X_{[2]} \in \mathbb{R}^{n * D_{model}} \tag{9}$$

Summing gives $X_{[2]}$, which needs to be normalized. The study uses layer normalization, i.e., for a given batch, normalization is performed across all feature dimensions. The formula is given below:

$$X_{[3]} = \frac{X_{[2]} - E\left[X_{[2]}\right]}{\sqrt{Var\left[X_{[2]}\right]}}, X_{[3]} \in n * D_{model} \tag{10}$$

2.2.2 Multi-attention mechanisms

In addition, a projection method based on multi-head attention mechanism is proposed in the transform framework, and the structure of the multi-head attention mechanism is shown in Fig. 1. The multi-head attention mechanism is to project Q, K, V to a low-dimensional one operation, consider the case of having h heads, project Q, K, V to columns of D_{model} / h dimensions by linear transformation respectively, and get Q_i, K_i, V_i respectively, compute the attention mechanism respectively and then merge them together. After learning separately, $X_{[3]}$ can be obtained after combining by W_0 matrix.

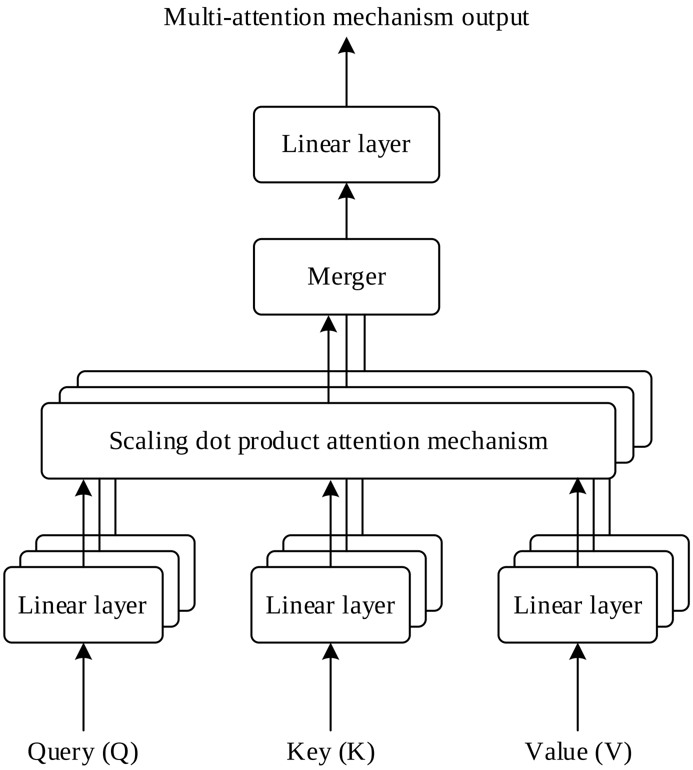

Figure 1: Multi-focus mechanism structure

$$Multihead(Q, K, V) = Concat\left(head_1, \ldots, head_n\right)W^O \tag{11}$$

where $head_i = Attention\left(QW_i^Q, QW_i^K, QW_i^V\right)$, and the projection method is by means of the parameter matrix $W_i^Q \in \mathbb{R}^{D_{model} \times d_k}, W_i^K \in \mathbb{R}^{D_{model} \times d_k}, W_i^V \in \mathbb{R}^{D_{model} \times d_v}$, where $d_q = d_k = \frac{D_{model}}{h}, W^O \in \mathbb{R}^{hd_v \times D_{model}}$.

In the case of considering h heads, keep the number of rows of Q, K, V unchanged and partition it according to the h dimension in the following way:

$$Multihead(Q, K, V) = Concat\left(head_1, \ldots, head_n\right)W^O \tag{12}$$

where $head_i = Attention\left(Q_i, W_i, V_i\right)$, this method is computationally small, faster to train, and increases the number of trainable dimensions and patterns.

2.2.3 Feedforward propagation layer

After passing through the self-attention mechanism layer, it is necessary to enter a feedforward propagation layer, which contains two sets of trainable parameters. The feedforward propagation layer is computed as:

$$FFN(x) = MAX\left(0, XW_1 + b_1\right)W_2 + b_2 \tag{13}$$

where X denotes the output of the previous layer, W_1 and b_1 are the first set of trainable parameters, and W_2 and b_2 are the second set of trainable parameters. The role of the feedforward propagation layer is to perform a nonlinear transformation of the input signal, thus improving the expressive power of the model.

2.2.4 Attention Mechanisms in Decoders

The structural components of the decoder are very similar to the encoder in that they are a combination of the attention mechanism, the feed-forward propagation layer, and the summation and normalization layer. In the decoder part, the implementation of the attention mechanism differs from the encoder in two ways:

a. In the decoder process, the self-attention mechanism is first accessed once. Unlike the encoder, the attention mechanism of the decoder requires the addition of masks for blocking out future sequences when computing the attention weights, thus allowing the model to be computed on sequences of different lengths.

b. After one self-attention mechanism computation and going through the summation and normalization layer, a second attention computation is required. The second attentional computation is not a self-attentional mechanism; the K and V matrices in this computation are derived from the output of the encoder. This step is called “reuse of the attention mechanism”, which can help the model to better utilize the information output from the encoder.

3 Research on the development of music disciplines with the intervention of the Music Intelligence Composition Model (MICM)

In this section, the intelligent music creation model based on the TRANSFORM framework designed above is embedded into the multimedia equipment in the music classroom as a means of realizing a pedagogical intervention experiment in music technological creation, and further exploring the impact of integrating with technology and creation on the future development of the music discipline.

3.1 Instructional case study research design

(1) Subjects

This investigation was conducted in a music academy, mainly targeting students in the class of 2024, from which 40 students were selected to carry out the teaching experiment of the Music Intelligence Composition Modeling Intervention.

(2) Data Acquisition Method

This study first understands the teaching process in the previous classroom, after which the learning effect after the lecture is further investigated, and the interview method is used to supplement the questionnaire survey of the students.

a. Classroom observation method, by listening to the classroom, the teaching process of the music classroom was observed to understand the state of the classroom atmosphere of teachers and students under the intervention of the Music Intelligence Creation Model.

b. Questionnaire survey method, centered on the investigation of students' demand for the music intelligent creation model, as well as the investigation of students' teaching effect and feelings towards the model after the practice. In the questionnaire, relevant questions are listed, mainly investigating the students' teaching effect and students' actual feelings after the intervention of the music intelligent composition model.

c. Theory test paper and teacher's assessment, through the test paper to understand the students' mastery of music theory knowledge, and then the teacher's assessment of the students' music skill level, in order to analyze the impact of music intelligent creation model on students' theory achievement and music skill level.

3.2 Factors influencing the development of the music discipline

The study is mainly based on the perspective of educational measurement theory to analyze the influencing factors of music discipline development. Through the music intelligence creation model intervention of the basic situation of music teaching and learning, its set of influencing factors as well as the measure of the development of the discipline, and then the quality of the collected data to ensure the reliability of the results, and finally the correlation between the various influencing factors and the development of the music discipline analysis.

3.2.1 Determination of impact factors

Individual students' perspectives mainly focus on the process factors of classroom feedback atmosphere, students' music core literacy, music theory achievement and skill level brought about by the music intelligence model to analyze the factors for the future development of the music discipline. Among them, the classroom feedback atmosphere includes four dimensions: interest, classroom activity, knowledge internalization and classroom participation. The core music literacy includes: aesthetic perception ability, artistic expression ability, cultural understanding ability, and creative practice ability. The music theory achievement and skill level included the final results of students' music examination and the evaluation of music skill level. The influencing factors of music subject development were identified as: interest, classroom activity, knowledge internalization and classroom participation, aesthetic perception, artistic expression, cultural understanding, creative practice, music theory achievement, and music skill level.

3.2.2 Metrics

Test papers are an effective medium for analyzing the effectiveness of teaching and learning. The final test was conducted at the end of a 3-month intervention of teaching the Music Intelligence Composition Model. The students' test papers as well as the data collected on various factors influencing the development of music discipline were used to analyze the factors of music discipline development. Each test was divided into a pre-test and a post-test, and the data from the pre-test and post-test were analyzed using a paired samples t-test to determine the effectiveness of the classroom intervention of the Music Intelligence Composition Model. The study will use questionnaires to collect data on classroom feedback climate, teaching and learning of music core literacy, and in analyzing students' theoretical performance and music skills through test papers and teacher assessments. The data collected from the questionnaires will be rated on a five-point Richter scale, while the theory scores and music skill levels will be rated on a percentage scale.

4 Analysis of the development of the music discipline based on intelligent creative modeling

4.1 Evaluation of the effectiveness of intelligent modeling of music composition

In order to demonstrate the effectiveness of the proposed model in music composition, this section compares this paper's music intelligent composition model with Recurrent Neural Networks (RNNs), Variational Auto-Encoders (VAEs), Generative Adversarial Networks (GANs), and Diffusion Models (DMs) in terms of both chord matching and musical harmony, and experiments are conducted using the LakhMIDI public dataset. In this context, chord matching is defined as an assessment of how similar the chords produced by the modeled samples are to the chords input from real samples. Harmony is defined as whether there are similar chords between tracks, and if the chord progressions are similar, the music is harmonized. In order to compare the fairness of the experiments, the experiments in this section use the same training dataset and the same test training set for all models, the same length of generation, and all models are measured 10 times to take the average value.
The results of the comparison of different models in terms of the overall effect of music generation are shown in Table 1. The comparison of the five models in terms of chord matching and musical harmony through the LakhMIDI dataset on the one hand not only concludes that the musical works created by this paper's model achieve the optimal results in terms of both the mean and the standard deviation. Compared with RNN, VAE, GAN, and DM, this paper's model improves chord matching by 10.4-20.2 percentage points and music harmony by 5.1-12.8 percentage points. And the standard deviation of 10 tests of this paper's model is smaller, which indicates that the consistency of its measurements is higher. From the above summary, it can be seen that the music intelligent creation model in this paper is stable and generates music with higher harmony and better quality.

Table 1: The comparison of the overall effect of different models in music

Models	Chord matching		Music harmony	
	Mean value	SD	Mean value	SD
Ours	0.653	0.025	0.559	0.023
RNN	0.549	0.033	0.492	0.044
VAE	0.521	0.029	0.431	0.031
GAN	0.503	0.037	0.508	0.036
DM	0.451	0.042	0.483	0.032

In addition, in order to verify the effectiveness of the works generated by the music intelligent creation model in terms of pitch and rhythm, this subsection will judge the effectiveness of the model in music generation based on the metrics of rhythmic correlation and pitch correlation. In terms of rhythm, two indicators are chosen, namely, the number of triplets (NCTN) and the qualified rhythmic frequency (QR), and in terms of pitch correlation, two indicators are chosen, namely, the number of pitch categories (UPC) and polyphony (PP).

Triplets: NCTN refers to the ratio of three consecutive notes with the same start and end times, and the ratio of consecutive identical notes to the total number of notes, the larger the ratio the more homogeneous the music.

Qualified Rhythmic Frequency: QR indicates the frequency at which the durations of notes within valid beats (1,1/2,1/4,1/8,1/16) are measured, their dots correspond to triplets, and any bound combination of two valid ratios.

Number of selected pitch categories: the number of pitches (from 0 to 12) used in each measure of the UPC, averaged over the musical fragment.

Polyphony: the ratio of the number of time steps in which the PP plays more than two notes to the total number of time steps. Ratio of the number of generated time steps to the total number of time steps.

The results of the comparison of different models in terms of note characteristics are shown in Table 2. In the triplet indicator, the model of this paper has the lowest score, only 0.244±0.013, which indicates that the music has a high diversity relative to other models. While in the qualified rhythmic frequency, the model score of this paper reaches 0.584±0.027, which is higher than the comparison model. According to the overall scores of both NCTN and QR, the musical works created by the model of this paper have obvious advantages in rhythm. In terms of the number of pitch categories and polyphony, the scores of this model are 0.752±0.033 and 0.651±0.038, which are higher than the other four models. It not only shows that the attention mechanism has obvious enhancement on music in terms of pitch and increases the diversity of music, but also shows that it has obvious advantages in terms of pitch diversity and can be applied to music teaching practice.

Table 2: Different models are compared to the characteristics of notes

Models	Mean±SD			
	NCTN	QR	UPC	PP
Ours	0.244±0.013	0.584±0.027	0.752±0.033	0.651±0.038
RNN	0.342±0.028	0.325±0.025	0.648±0.047	0.555±0.029
VAE	0.376±0.031	0.398±0.034	0.565±0.039	0.598±0.042
GAN	0.321±0.024	0.466±0.043	0.636±0.044	0.604±0.050
DM	0.358±0.019	0.431±0.029	0.554±0.033	0.583±0.035

4.2 Pedagogical Effects of the Music Intelligence Composition Modeling Intervention

In this section, through a pre- and post-test experiment, the pedagogical effects of the Music Intelligence Creation Model for music subject education are explored in terms of music classroom feedback climate, students' core music literacy, and students' theoretical achievements and skills.

4.2.1 Classroom feedback climate

In this section, by communicating with students and analyzing the suggestions of the listening teacher after class, we compare the pre-test and post-test effects of lesson feedback of 40 students from the four dimensions of interest, classroom activity, knowledge internalization and classroom participation, aiming to study whether the Music Intelligence Creation Model has some value and effect on the optimization of the classroom feedback atmosphere in the discipline of music.

The pre-test and post-test effects of music classroom feedback atmosphere are shown in Figures 2 and 3, respectively. Combining the two figures, it can be found that the students' classroom feedback performance before teaching is not particularly good, with the average scores of interest, classroom activity, knowledge internalization and classroom participation at 3.47, 3.25, 3.14 and 3.43, respectively.With the teaching experiment, the students' classroom feedback has been improved in each index, with the average score ranging from 3.99 to 4.69 points. Paired-sample t-test statistical analysis yielded that the difference between the mean scores of 40 students' interest, classroom activity, knowledge internalization and classroom participation on the pre- and post-tests ranged from 0.60 to 1.26 and was statistically significant ($p < 0.05$). The integration of the music intelligence creation model into music subject education obviously improved the atmosphere of the classroom, increased the interaction between teachers and students, and made the music class more vivid and lively. At the same time, it is also an opportunity for students to consolidate and apply what they have learned again.

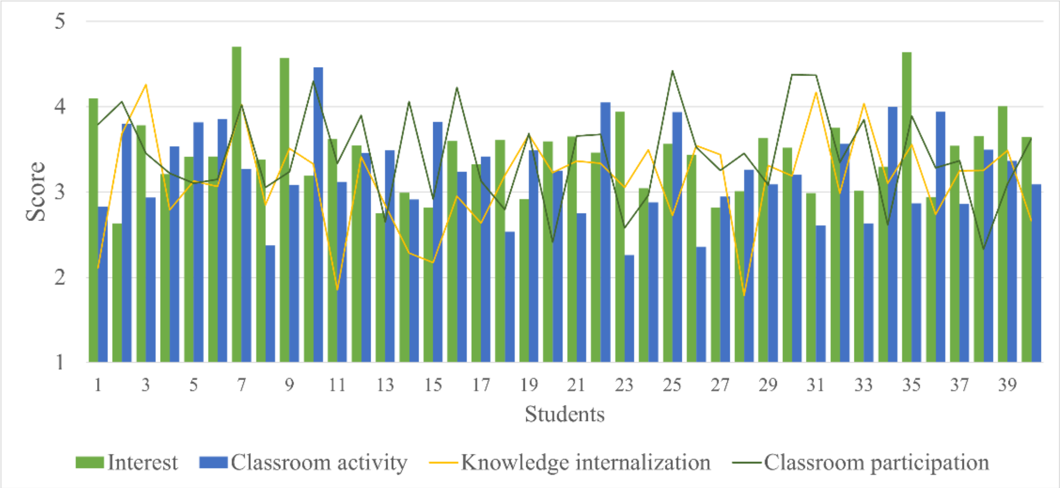

Figure 2: The music class feedback atmosphere of pre-test

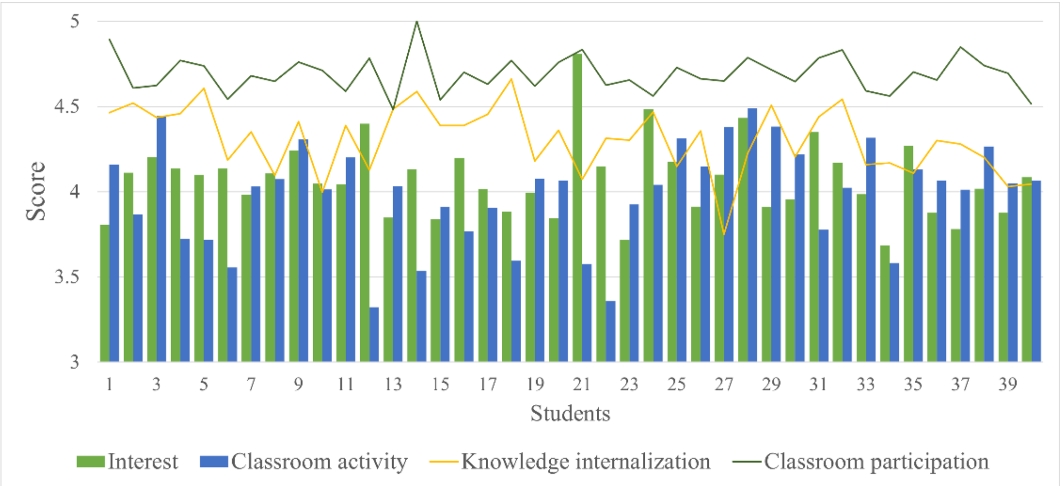

Figure 3: The music class feedback atmosphere of post-test

4.2.2 Core music literacy

The main purpose of this investigation was to find out whether the core literacy skills of 40 students were improved in music teaching under the intervention of the Music Intelligence Creation Model by distributing and analyzing the learning outcomes questionnaire. The questionnaire was divided into four dimensions: aesthetic perception ability, artistic expression ability, cultural understanding ability, and creative practice ability. The questionnaires were distributed before and after the teaching implementation respectively, and the collected pre-test and post-test data and retrograde analysis were analyzed using SPSS software to verify the effectiveness of the Music Intelligence Creation Model based on music education.

After a 3-month music teaching based on the Music Intelligence Composition Model for 40 students, the core literacy level of the 40 students was measured, and Figures 4 and 5 show the results of the pre-test and post-test of each of the investigated dimensions of the core literacy of the students, respectively.The average scores of each index of the core literacy of the 40 students did not exceed 3.5, with the Creative Practicality scoring the highest, with an average score value of 3.48. At the end of the comparative teaching, the core literacy indicators improved significantly, with the average score value ranging from 3.88 to 4.52. Comparing the pre-test and post-test data of 40 students through the paired-sample t-test method, the results show that in the music classroom based on the Music Intelligence Composition Model, the mean values of the students' core literacy indicators increased by 0.84~1.24, and there is a significant difference in the comparison of the indicators ($p<0.05$). This data indicates that the application of the music intelligence creation model to music education in colleges and universities has indeed significantly improved students' core literacy in music learning.

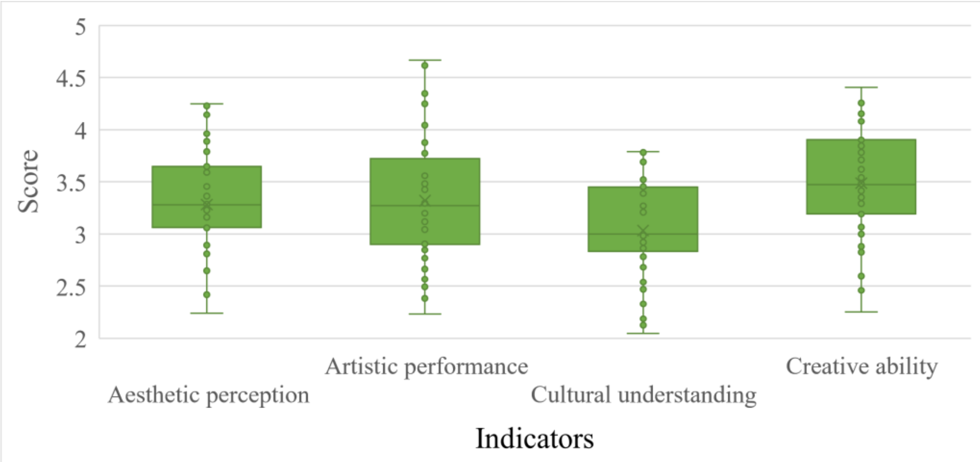

Figure 4: The results of the survey indicators of the pre-test

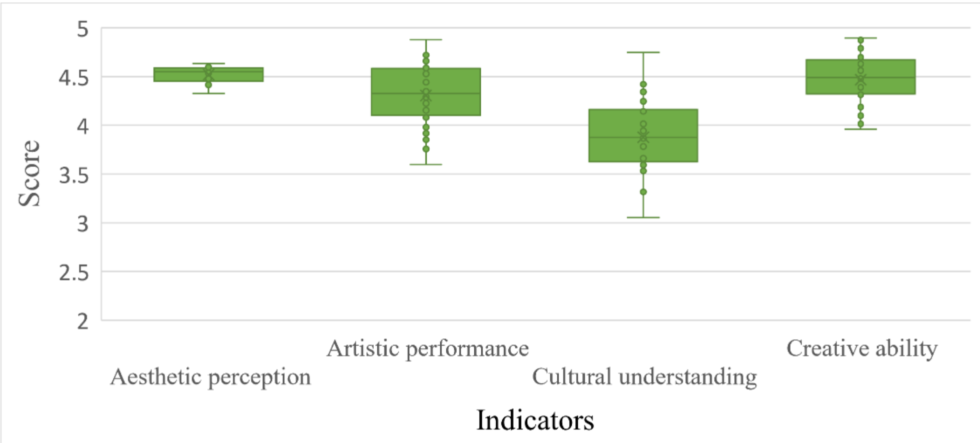

Figure 5: The results of the survey indicators of the post-test

4.2.3 Music theory and skills

In the process of music learning, teacher's evaluation is an important part, which can effectively promote and guide students' learning. In this section, 40 students were evaluated on both their music theory grades and music skill levels to analyze the practical value of the Music Intelligence Creation Model in music subject education. Teachers were invited to score the students' final grades in order to make the grades more accurate and the evaluation results free from subjective opinions.

The comparison of students' music scores before and after the implementation of the Music

Intelligence Creation Model is shown in Figures 6 and 7, respectively. Before and after the implementation of the Music Intelligence Creation Model, there was a significant difference between the music theory scores and music skill levels of the 40 students. Among them, before the implementation of the Music Intelligence Creation Model for music teaching, the average theory score of the 40 students was only 75.03, and the average music skill score was only 69.1. After three months of the Music Intelligence Creation Model intervention, the students' average theory scores and music skill scores increased to 84.10 and 81.78, respectively, which fully demonstrated that the application of the Music Intelligence Creation Model in music teaching had achieved good pedagogical results.

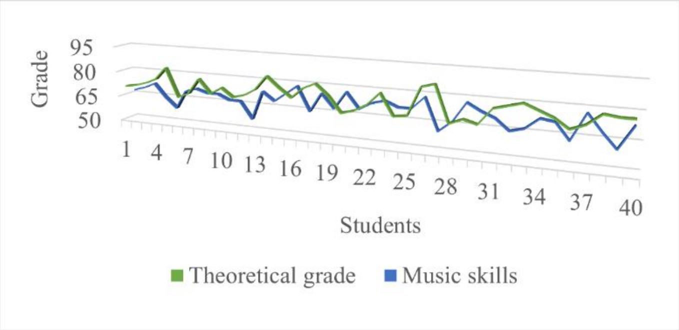

Figure 6: Student music theory of pre-test

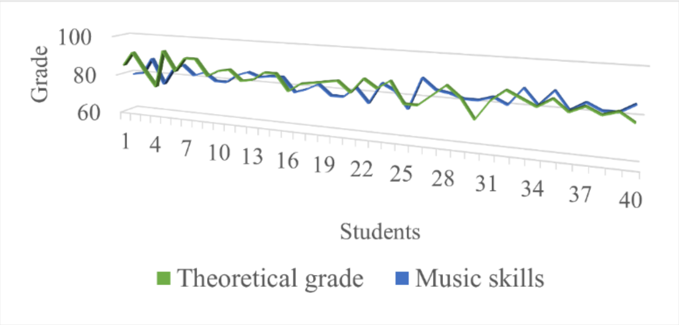

Figure 7: Student music theory of post-test

4.3 Relevance of the Intelligent Composition Model to the Development of the Music Discipline

This subsection focuses on the analysis of the influence of the music intelligence model on the development of the music discipline, based on the results of the descriptive analysis of the teaching and learning outcomes of the music intelligence model, and establish its regression model with the development of the music discipline, in order to explore the factors of the influence of the music intelligence model on the music discipline.

The independent variable consists of three parts, which are classroom feedback, core literacy, and related variables of theory and skills, which are recorded as model 1~3 in turn, and the dependent variable is the development of music discipline, through which the future development trend of music discipline is expressed. The regression method was used to determine the significance of the correlation between all the subcomponents of the three variable models and the stratified regression analysis of music discipline development. The results of the regression analysis of all the subcomponents of the model of music intelligence creation with music discipline development stratification are shown in Table 3.

Classroom Feedback, Model 1: This variable explained 41.2% of music discipline development, and the regression effect of Model 1 was significant at the 0.001 level of significance (F=218.496, p<0.001). All the items under it, i.e., interest, classroom activity, knowledge internalization and classroom participation, had varying degrees of influence on the development of the music discipline, with β ranging from 0.273 to 0.603, which was significant (p<0.01).

Music core literacy, model 2: The items included in this variable are: aesthetic perception ability, artistic expression ability, cultural understanding ability, and creative practice ability. The degree of explanation for the development of the music discipline was 37.2%, and the regression effect of model 2 was significant at the 0.001 significance level (F=183.742, p<0.001). The level of influence of each subvariable exceeded 0.4 and was significant (p<0.01) for the development of music discipline.

Theory and Skills, Model 3: This model explains 46.7% of the development of the music discipline, and the regression effect of Model 3 is significant at the 0.001 level of significance (F=134.498, p<0.001). At the 0.001 significance level, the effect of theory grades on the development of the music discipline was significant (β=0.486, p<0.001), and the effect of music skill level on the development of the music discipline was significant (β=0.672, p<0.001).

The explanatory power of all the subcomponents of the model of musical intelligence creation on the development of music discipline was more than 35% and the standardized coefficients β were all positive, i.e., the model of musical intelligence creation had a direct effect on the development of music discipline.

Table 3: The analysis of the hierarchical regression of all items and music department

Variable		Normalization factor		t	F	R^2
		β	Standard error			
Classroom feedback (Model 1)	constant			14.798**	218.496***	0.412
	Interest	0.273	0.028	18.108***		
	Classroom activity	0.603	0.032	19.874***		
	Knowledge internalization	0.425	0.009	17.754***		
	Classroom participation	0.295	0.012	18.654**		
Core accomplishment (Model 2)	constant			8.528*	183.742***	0.372
	Aesthetic perception	0.518	0.024	12.987**		
	Artistic performance	0.401	0.013	7.274**		
	Cultural understanding	0.514	0.015	17.981**		
	Creative ability	0.486	0.013	20.619***		
Theory and skills (Model 3)	constant			16.76**	134.498***	0.467
	Theoretical grade	0.486	0.037	11.539***		
	Music skills	0.672	0.025	19.382***		

Note: *p<0.05, **p<0.01, ***p<0.001

5 Conclusion

This paper is based on the research on the integration of technology and music creation, for which a music intelligent creation model is designed. The music intelligent creation model is centered on the TRANSFORM framework, which transforms music data into matrix form through data embedding and location information encoding. The attention mechanism and feed-forward propagation layer cooperate with each other to empower and nonlinearly transform the notes, which in turn improves the performance of the model music creation. The model is introduced into music teaching practice to explore the impact of the music intelligent composition model on the development of music discipline through classroom feedback, core literacy and other indicators.

The music intelligent composition model performs well on the public dataset and outperforms the comparison model in terms of chord matching, musical harmony, and generating note features. Applying the model, students' classroom feedback performance scores exceeded 3.9, significantly higher than before the teaching experiment. In addition, students' core music literacy was also significantly improved, with increases in each indicator ranging from 0.84 to 1.24 points. Meanwhile, students' average music theory scores and music skill levels were significantly higher than before the model was applied. The results of the regression analysis showed that classroom feedback atmosphere, music core literacy, and music theory and skills all contributed to the development of the music discipline at the 0.001 significant level.

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