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Interdisciplinary Model Construction for the Integration of Chongqing Ethnic Music and Hongyan Culture

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SUMMARY: *Red Rock Culture is an important spiritual pillar that once motivated and inspired a generation of Chinese people, however, it seems to be seldom mentioned in today's highly developed market economy. This paper focuses on the fusion of Chongqing folk music and red rock culture, and takes the construction of learners' music learning ability as the entry point, selects the music majors of Chongqing undergraduate colleges and universities from freshmen to sophomores to conduct a questionnaire survey, and constructs an evaluation system of the ability of music majors. Factor analysis method and model clustering method are used for analysis. The results of the study show that students' music learning ability mainly consists of professional skills, humanistic literacy, career development and emotional value, with a cumulative explained variance percentage of 66.125%, and the clustering results classify the types of students' ability into relatively superior ability and good thinking type, versatile ability and less resourcefulness type, and low ability and mediocrity type. Based on the above, the study further constructs a STEAM interdisciplinary teaching model oriented to the integrated teaching of Chongqing folk music and Hongyan culture through STEAM education concepts, which provides an innovative path for the inheritance of Hongyan culture and folk music.*

KEYWORDS: *factor analysis; fuzzy clustering; red rock culture; STEAM education; teaching mode*

1 Introduction

Interdisciplinary integration is an important trend in today's educational development, the core of which lies in breaking the boundaries between traditional disciplines, encouraging in-depth thinking and comprehensive analysis from multiple perspectives, and innovating the form of resource application and improving the utilization rate of resources by exploring and solving practical problems [1-4]. In order to achieve this goal, it is necessary to draw on the essence of various disciplines and systematically integrate the knowledge of different fields around a specific theme, thus building a three-dimensional knowledge structure. Interdisciplinary integration has had a profound impact on the traditional concept of music. The traditional mode of music composition often focuses on single musical skills and music theory knowledge, ignoring the connection between music and other disciplines [5, 6]. And interdisciplinary fusion in music creation can combine music with other disciplines, so as to make music richer and more diverse, and improve the value and charm of music [7, 8].

Chongqing was known as “Ba Guo” in ancient times, and was shortened to “Yu” after the direct administration. Bayu land mountains and rivers, rivers running, humanities, beautiful scenery, local folk music from the life of the people of all nationalities, “see the mountains sing

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mountains, water sing water", not only reflects the characteristics of folk music with the music, but also reflects the wisdom of the people, is colorful, fascinating [9-12]. The red rock culture originated in Chongqing is a valuable red spiritual wealth of the Chinese communists and the Chinese nation, which is of great commemorative significance and inheritance value to the whole country and society [13]. At present, the red rock culture faces the challenge of inheritance and dissemination. While culture mostly serves as the source of inspiration and creative background of music, music serves as a living form of cultural dissemination, and there is a commonality between the two [14, 15]. Under the background of interdisciplinary integration, the interdisciplinary integration of Chongqing folk music and Hongyan culture helps to realize the value enhancement and inheritance innovation of both.

The study takes music majors from freshmen to sophomores in Chongqing undergraduate colleges and universities as samples, and conducts questionnaire surveys online and offline to determine the evaluation index system that includes four dimensions: professional skills, humanistic qualities, career development, and emotional value. For each index dimension, the common factor was extracted by factor analysis method, while three types of students based on music learning ability were obtained by using fuzzy clustering. According to the research content on the basis of STEM teaching model, 5EX model, and C-STEAM teaching model, the STEAM interdisciplinary teaching model oriented to the integration teaching of Chongqing folk music and Hongyan culture is constructed.

2 Constructing a Portrait of Chongqing Ethnic Music Learning Ability Toward the Red Rock Culture

2.1 Subjects of study

Selected 1 Chongqing undergraduate colleges and universities freshman to sophomore music majors, take the network and offline way to investigate the degree of understanding of the red rock culture and the students' music knowledge, May 1, 2025 a total of 584 questionnaires were issued, June 29th to complete the effective questionnaire survey of the factors affecting the students' music learning ability 411 copies.

2.2 Selection of indicators

This paper draws on existing literature, interviews undergraduate college freshman to sophomore music majors, and builds an evaluation index system around the two core dimensions of "Red Rock Culture Cognition" and "Ethnic Music Learning Ability" as shown in Table 1.

Table 1: Evaluation Index Dimensions and Specific Indicators

Dimension	Indicator number	Indicator Description
Professional skills	1	Instrumental performance skills
	2	Mastering music theory
	3	Stage expressiveness
Humanistic quality	4	Historical knowledge
	5	Art appreciation ability
	6	Cultural understanding
Vocational development	7	Awareness of career planning
	8	Internship experience
	9	Employment competitiveness
	10	Teamwork
Emotional value	11	Cultural identity
	12	Learning motivation intensity

2.3 Research methodology

2.3.1 Factor analysis

Factor analysis is a generalization of principal component analysis and an inverse problem of principal component analysis. Factor analysis is a modeling method that uses a few representative factors to reflect the relationship between the overall multiple indicators, and divides the categories according to the density of the relationship between the factors, so as to redefine the factor categories for the purpose of dimensionality reduction to reflect most of the overall information. Specifically, the original variables are decomposed and the original variable covariance matrix is constructed, and when the number of extracted common factors is the same as that of the original variables, the factor analysis carries out the corresponding variable transformation. Let $X_i\left(i=1,2,\cdots,p\right)$, p variables, be expressed by equation (1):

$$\begin{cases} X_1=\mu_1+\alpha_{11}F_1+\cdots+\alpha_{1m}F_m+\varepsilon_1 \\ X_2=\mu_2+\alpha_{12}F_1+\cdots+\alpha_{2m}F_m+\varepsilon_2 \\ \qquad\vdots \\ X_p=\mu_p+\alpha_{p1}F_1+\cdots+\alpha_{pm}F_m+\varepsilon_p \end{cases} \tag{1}$$

The matrix relationship can be expressed by equation (2) as follows:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}=\begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix}+\begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{p1} & \alpha_{p2} & \cdots & \alpha_{pm} \end{bmatrix}\begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix}+\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{2}$$

where $F_1,F_2,\cdots,F_m$ are the common factors, which are called unobservable variables, and whose coefficients are called factor loadings. The ε_i is the special factor, the part that cannot be included by the first m public factors. The matrix A is called the factor loading matrix and is shown in (3):

$$A = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{p1} & \alpha_{p2} & \cdots & \alpha_{pm} \end{bmatrix} \tag{3}$$

It is necessary to satisfy the requirement that the number of common factors of $F_1, F_2, \cdots, F_m$ is less than or equal to the number of original variables, p, and also the following requirements:

(1) $\mathrm{cov}(F, \varepsilon) = 0$, and the common factor F and the special factor between ε are for independent of each other, i.e., uncorrelated;

(2) $D(F) = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix} = I$ i.e., $F_1, F_2, \vdots, F_m$ are two-by-two uncorrelated and each variance F_i is 1;

(3) $D(\varepsilon) = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_p^2 \end{bmatrix}$ indicates that the two are uncorrelated and the variances may be equal;

If $\varepsilon_i \sim N(0, \sigma_i^2)$ satisfies the above conditions, it is called an orthogonal factor model. If equation (2) does not hold, i.e., $D(F) \neq I$, and the common factors are not independent of each other, the factor analysis model is a skewed factor model. Generally speaking, for each original variable, its factor loading matrix, the loadings on one common factor is larger, and the loadings on other common factors are smaller, the situation is the most ideal. If the loadings of the original variables on each common factor cannot be effectively differentiated, the loadings of the original variables on each common factor can be further adjusted by the factor rotation method to make the original variables as effectively differentiated as possible, and the larger the factor loadings, the greater the degree of explanation of the original variable for the new common factor.

2.3.2 Cluster analysis

In statistics, cluster analysis refers to the categorization of the object to be studied. The difference between cluster analysis and discriminant analysis lies in the fact that discriminant analysis is also a classification method, but discriminant analysis knows the number of categories and the characteristics of each category before classification, and all that needs to be analyzed is that the samples of the unknown categories are correctly attributed to one of the categories. But cluster analysis in the classification before the number of categories do not know, more do not know the specific categories of the observed samples, the analysis of these data samples into samples and samples or classes and classes between the distance between the distance, choose a metric to measure this distance, and then according to the distance of the relationship between the distance is close to the distance is also close to the object is categorized as a class, the distance of objects between the different classes are relatively Far away, this is the common idea of cluster analysis methods.

There are two types of cluster analysis, Q-type cluster analysis and R-type cluster analysis, Q-type cluster analysis for the clustering of samples, which refers to the similar samples into a class; R-type clustering of the classification object is a variable, the similar variables together. According to the method of clustering cluster analysis can be divided into systematic clustering method, dynamic clustering method, optimal segmentation method, fuzzy clustering method, graph theory clustering method, cluster forecasting method and so on. This paper mainly introduces the systematic clustering method.

Systematic clustering method is a clustering method used more often in the cluster analysis method, it will firstly look at each sample individually as a class, select a method to specify the distance between the classes, and then go to select the distance between the minimum of the two samples will be merged into a new class, and then continue to calculate the merger of the distance between the new class and the other classes, and then the distance between the nearest two classes are merged into a new class, and so on, so that after each completion, there will be one class less than the other. Each time after the completion of the class will be reduced by one, until finally all the samples are merged into one class when to stop. Commonly used distances include absolute value distance, Euclidean distance, Ming's distance, Chebyshev's distance, Ma's distance, Lang's distance, cosine distance and so on. At the same time, the systematic clustering method in defining the distance between classes in addition to the commonly used method of class averaging there is the shortest distance method, the longest distance method, the center of gravity method, the intermediate distance method, the sum of squares of the deviation method and so on.

This article is about the principle of the sum of squares of departures method. Let G_K and G_L be merged into a new class G_M, then the sum of squares of the departures of G_K, G_L, and G_M are respectively:

$$W_K = \sum_{i \in G_K} (x_{(i)} - \overline{x_K})^T (x_{(i)} - \overline{x_K}) \tag{4}$$

$$W_L = \sum_{i \in G_L} (x_{(i)} - \overline{x_L})^T (x_{(i)} - \overline{x_L}) \tag{5}$$

$$W_M = \sum_{i \in G_M} (x_{(i)} - \overline{x_M})^T (x_{(i)} - \overline{x_M}) \tag{6}$$

where $\overline{x_K}$, $\overline{x_L}$ and $\overline{x_M}$ are the centers of gravity of G_K, G_L and G_M respectively. So W_K, W_L and W_M reflect the dispersion of the respective class samples. If the distance between the classes G_K and G_L is relatively small, the sum of squared deviations $W_M - W_K - W_L$ added by combining them should be relatively small; otherwise, the sum of squared deviations added should be relatively large. Thus the squared distance between G_K and G_L is defined as:

$$D_{KL}^2 = W_M - W_K - W_L \tag{7}$$

This method of specifying distances between classes in systematic clustering is known as the sum-of-squares method.

3 Findings and analysis

3.1 Empirical analysis of the structure of music learning ability

(1) KMO and Bartlett's test of sphericity

The KMO sampling suitability measure was measured to be 0.841, which is greater than 0.8; the Bartlett's test of sphericity approximate chi-square value was 2085.729, which passed the 0.001 significance test, thus indicating that the scale data are suitable for further factor analysis.

(2) Explained total variance

The total variance explained is shown in Table 2, a total of 12 factors were extracted as principal components for the students' music learning ability scale, and a total of 3 factors with initial eigenvalues greater than 1 were extracted, with a cumulative explained variance of 66.125%. It indicates that the 3 main factors extracted are qualified for the interpretation of the original data. The eigenvalue of factor 1 is 3.764 and the percentage of explained variance is 32.358%, the eigenvalue of factor 2 is 2.016 and the percentage of explained variance is 15.775%, and the eigenvalue of factor 3 is 1.218 and the percentage of explained variance is 9.242%.

Table 2: Total variance explained

Ingredient	Initial eigenvalue			Sum of squares of rotational loads		
	Amount to	variance percentage	Accumulate%	sum of squares of rotational loads	sum of squares of rotational loads	sum of squares of rotational loads
1	3.764	31.367	31.367	3.883	32.358	32.358
2	2.016	16.800	48.167	1.893	15.775	48.133
3	1.218	10.150	58.317	1.109	9.242	57.375
4	0.937	7.808	66.125	1.05	8.750	66.125
5	0.822	6.850	72.975			
6	0.701	5.842	78.817			
7	0.653	5.442	84.259			
8	0.504	4.200	88.459			
9	0.444	3.700	92.159			
10	0.413	3.442	95.601			
11	0.305	2.542	98.143			
12	0.223	1.858	100			

(3) Gravel diagram

The gravel plot is shown in Figure 1. The inflection points of the music learning ability scale for music majors appeared at 4, again indicating that it is more reasonable to extract 4 main factors from the 12 factors.

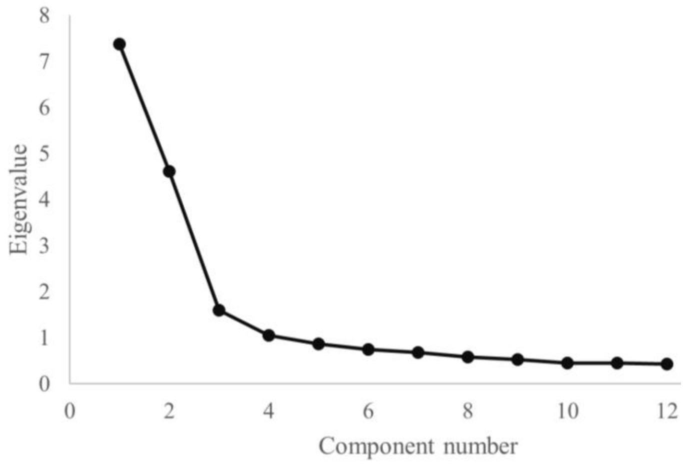


Figure 1: Gravel Map

(4) Rotated Component Matrix Analysis

Rotated component matrix analysis is able to represent seemingly unrelated factors as linear forms of major factors. In general, factor loadings greater than 0.5 are attributed to that major factor, and the rotated component matrix is shown in Table 3. From the rotated component matrix in Table 3, it can be seen that each major factor has a high degree of dependence on the included factors. The loadings of each factor on its major factor have more desirable values, ranging from a minimum of 0.511 to a maximum of 0.833.

Table 3: The rotated component matrix a

	Ingredient			
	Professional Skills	Humanistic Quality	Career Development	Emotional Value
Instrumental performance skills	0.821			
Mastering music theory	0.679			
Stage expressiveness	0.574			
Historical knowledge		0.641		
Art appreciation ability		0.869		
Cultural understanding		0.833		
Awareness of career planning			0.511	
Internship experience			0.793	
Employment competitiveness			0.755	
Teamwork			0.739	
Cultural identity				0.644
Learning motivation intensity				0.693

(5) Validation factor analysis

The results of the validation factor analysis are shown in Table 4. The validation factor analysis found that: the value of the three-factor model X2/df is 2.002, less than 3, good fit; RMSEA is 0.051, less than 0.08, good fit; NFI is 0.913, greater than 0.9, good fit results; RFI is 0.925, greater than 0.9, good fit results; IFI is 0.906, greater than 0.9, good fit results TLI was 0.953, greater than 0.9, with good results; CFI was 0.961, greater than 0.9, with good results. On the whole, the 12 factors of music ability scale for music majors extracted 3 main factors optimally, and professional skills, humanistic qualities, career development, and emotional value have a better representation of music learning ability of music majors in undergraduate colleges and universities.

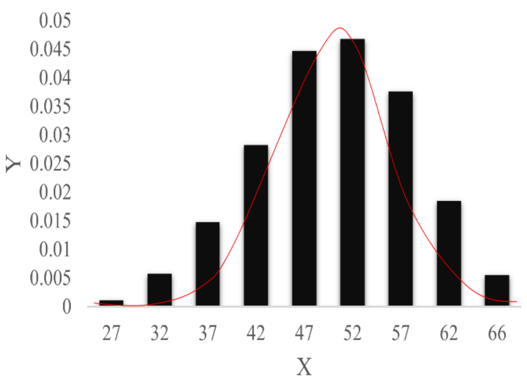
Table 4: Confirmatory factor analysis results

Fitting index	X2/df	RMSEA	NF I	RF I	IFI	TLI	CFI
Fitting criteria	(1,3)	<0.07	>0.09	>0.09	>0.09	>0.09	>0.09
Single factor model	6.144	0.092	0.833	0.839	0.813	0.891	0.872
Two factor model	5.391	0.085	0.829	0.877	0.829	0.851	0.867
Three factor model	2.022	0.051	0.913	0.925	0.906	0.953	0.961

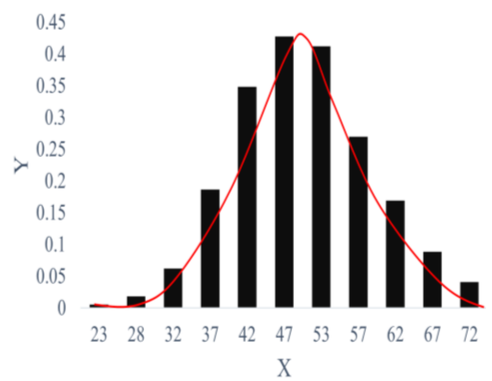
3.2 Sample Cluster Analysis

3.2.1 Distribution of capacity

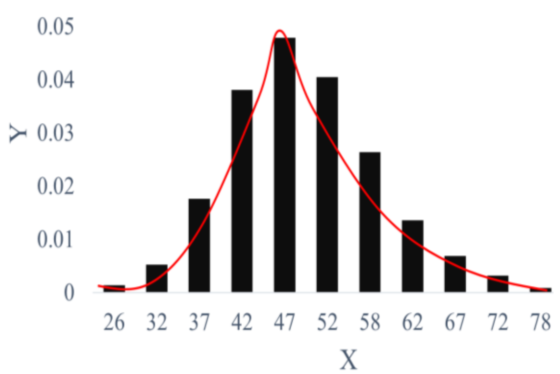
In this study, model clustering was used to cluster and analyze the competency measurement data of the sample, and the metrics used for clustering were the measured competencies of the graduates. From the perspective of competency measurement, the distribution of each competency in the population should be normal, and the distribution of multiple competency measurement data is most likely to obey a finite Gaussian mixture model. The distribution of the four competency scores is shown in Figure 2. Observation of the distribution of the four competencies of professional skills, humanistic qualities, career development and emotional values reveals that all four competencies are close to normal curves, so this data is suitable for the use of model clustering method.



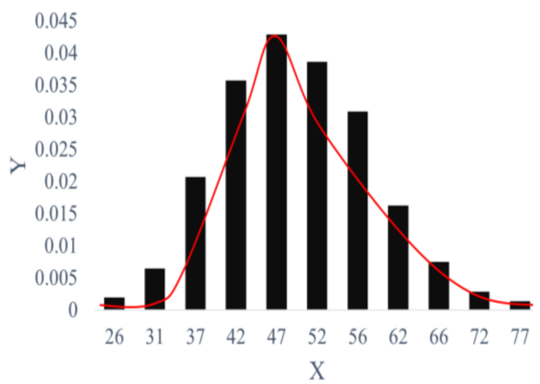
(a) Professional skill score



(b) Humanistic literacy ability score



(c) Career Development Competency Score



(d) Emotional Value Ability Score

Figure 2: Distribution of scores for the four abilities

The model clustering method assumes that the data come from a mixture of distributions of one or more components (categories), based on the characteristics of the data, this study assumes that the music learning ability of music students obeys a multidimensional Gaussian mixture of distributions, and there may be several distributions of different characteristics in the student population, and the purpose of this study is to find these distributions (categories). A Gaussian distribution can be described by a mean, variance-covariance matrix. Individual distributions are concentrated at their mean, with higher densities the closer they are to the mean (an analogy can be made to the density curves of individual abilities). Its variance-covariance matrix determines the geometric characteristics of the category, such as shape, size, orientation, etc. With this information, it is possible to calculate the likelihood that any observation within the sample is from a particular category.

The model clustering method is divided into three specific steps: randomly selecting Gaussian distribution parameters to fit the data points under a specific model, iterating the parameters of the distribution to fit more data until the iterations make the changes in the parameter values converge, and calculating the distance of the data in the data from the individual points from the distribution to place the points that are close to the distribution in the category. In this study, the data were analyzed using the mclust library (version 5.4), which utilizes the Maximum Expectation Algorithm for parameter iteration.

3.2.2 Cluster analysis

(1) Selection of ability indicators

The above measurement of students' music learning ability gives a total of 12 indicators in 4 categories of ability, including 3 professional skills ability, 2 humanistic ability, 4 career development ability, and 2 emotional value ability. The more indicators used, the larger the sample size required to obtain effective clustering. Comparing the overall indicators of music learning ability with the sub-dimension indicators, it was found that the Pearson correlation coefficients of the overall ability indicators with music theory mastery, stage performance, cultural understanding, teamwork ability and cultural identity were 0.719, 0.187, 0.639, 0.672, and 0.651, respectively, and all of them were significant at 1% level, and the problem solving based on the one-factor model and the multifactor model were significant at 1% level. competence indicators have Pearson correlation coefficients as high as 0.972 and are significant at 1% level, so it can be assumed that the competence indicators based on the single-factor model can represent the sub-dimensional indicators and multi-factor indicators.

(2) Unidimensional competency type identification

Firstly, the four unidimensional competence indicators were analyzed by clustering respectively, and the clustering results are shown in Table 5. The clustering results show that the overall distribution of critical thinking competence can be fitted by two homoskedastic subdistribution types, with a mean of 55.13 for subclass A and a mean of 45.24 for subclass B competence; the model clustering gives the possibility that the sample observations come from both subclasses. The overall distribution of humanistic competence can be fitted by 5 homoskedastic subdistribution types with means of 64.03, 54.19, 52.31, 43.51, and 31.43 with a standard deviation of 4.88 for subclasses A to E. This shows a large intergroup variation in students' humanistic competence, with the difference in the means between subclasses A and E being as high as 7.11 standard deviations.

Table 5: One-dimensional capability clustering results

Model information	Professional skills	Humanistic quality	Vocational development	Emotional value
Mixed probability	(61.16%, 40.11%)	(15.08%,25.43%,23.13%, 35.04%,2.79%)	(20.29%, 81.21%)	(33.65%, 67.05%)
Subclass information	(Mean, Standard Deviation) Sample size, uncertainty			
Subclass A	(55.13,6.76%) 249,18.12	(64.03,4.88) 241,21.09%	(60.22,7.17) 593,20.73%	(57.06,7.36) 209,18.7%
Subclass B	(45.24,6.76%) 131,24.02	(54.19,4.88) 193,19.1%	(48.19,7.17) 375,19.59%	(47.19,7.36) 179,19.2%
Subclass C		(52.31,4.88) 173,20.4%		
Subclass D		(43.51,4.88) 373,21.09%		
Subclass E		(31.43,4.88) 70,20.5%		

3.2.3 Clustering results

In order to exclude the probabilistic factors of the distribution from influencing the typicality of the types and to deepen the understanding of the distribution of each type of ability, we first observe the distribution of each unidimensional ability type in each multidimensional ability type, and then analyze the relationship between the multidimensional abilities, and the results of the analysis are shown in Figure 3. It can be seen that the percentage of each high unidimensional competence type in Type 1 is about 19% or so lower than its average proportion in the total sample. Almost all of the samples in Type 2 are high professional skill types, high career development type is almost indistinguishable from the total sample ratio, and the proportion of high emotional value is higher than the average sample. Type 3 has a higher than average proportion of high unidimensional competency types except for professional craft.

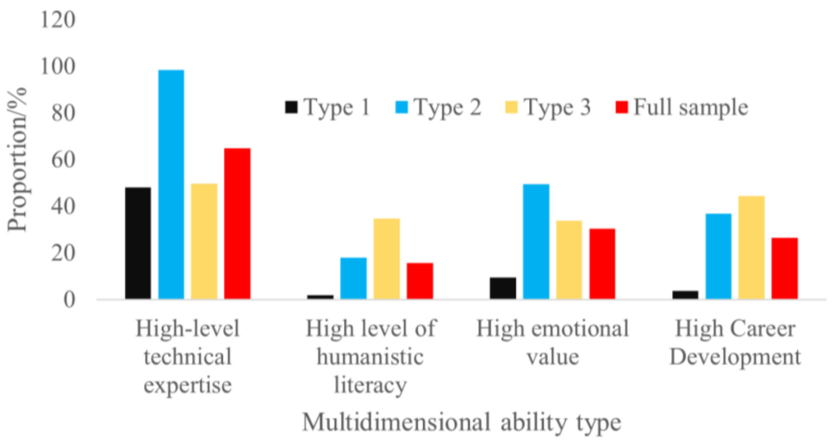


Figure 3: The proportion of high ability single type in multidimensional ability type

3.3 Capacity characterization

In this section, students' music learning ability types are classified into three types: more competent and good thinker, more competent and less resourceful, and less competent and mediocre. By comparing the performance of the three types of students in the music learning ability assessment, and the similarities and differences of the unidimensional ability types in the internal distribution of the types, the characteristics of each type of student are summarized.

Table 6 shows the correlation coefficients between the probability of observing each type and all the ability measures, and the correlations between these probabilities and all the ability measures are significant at the 0.01 level, except for type 3 and the sub-dimension of "internship experience".

Table 6: Correlation between ability scores and type probabilities

Feature	probability of superior thinking (mean=31.7%)	probability of being versatile and not scheming (mean=33.28%)	low energy mediocre type probability (mean=34.95%)
Instrumental performance skills	0.715**	-0.171**	-0.401**
Mastering music theory	0.392**	0.443**	-0.704**
Stage expressiveness	0.088**	0.209**	-0.256**
Historical knowledge	0.083**	0.079**	-0.137**
Art appreciation ability	0.171**	0.306**	-0.409**
Cultural understanding	0.177**	0.227**	-0.341**
Awareness of career planning	0.081**	0.236**	-0.276**
Internship experience	1.181**	0.365	-0.469**
Employment competitiveness	0.089**	0.094**	-0.227**
Teamwork	-0.149**	-0.209**	0.304**
Cultural identity	0.331**	0.307**	-0.535**
Learning motivation intensity	0.356**	0.317**	-0.561**

**: indicates that the correlation is significant at the 0.01 level (two-tailed)

4 Chongqing Ethnic Music STEAM Teaching Model for Red Rock Culture

4.1 STEM teaching model

According to the results of the above research from the theoretical support, teaching tasks, teaching steps, teaching summary, and other conditions of the five aspects of the analysis of STEM teaching, the teaching task is to improve the students' STEM ability, the teaching task is to improve the students' STEM ability, to establish a new model of teaching as shown in Fig. 4, and it is in line with the concept of STEM education.

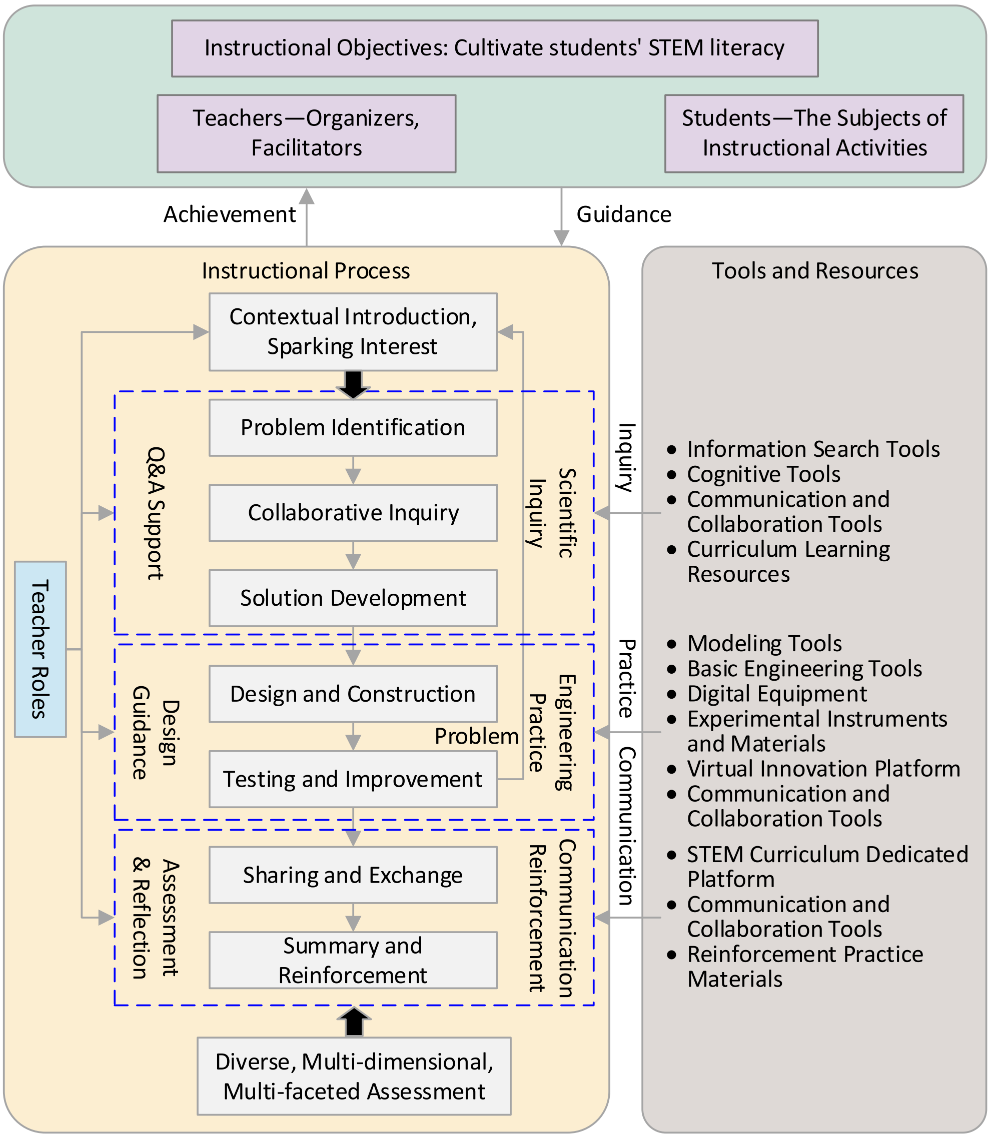


Figure 4: STEM teaching model

4.2 Interdisciplinary STEAM Teaching Model Construction

Based on constructivist learning theory, project-based learning theory, contextual learning theory, in STEM teaching model, project-based interdisciplinary learning activity design 5EX model, C-STEAM teaching model. The interdisciplinary teaching model oriented to the integration of Chongqing folk music and Hongyan culture teaching was constructed as shown in Figure 5.

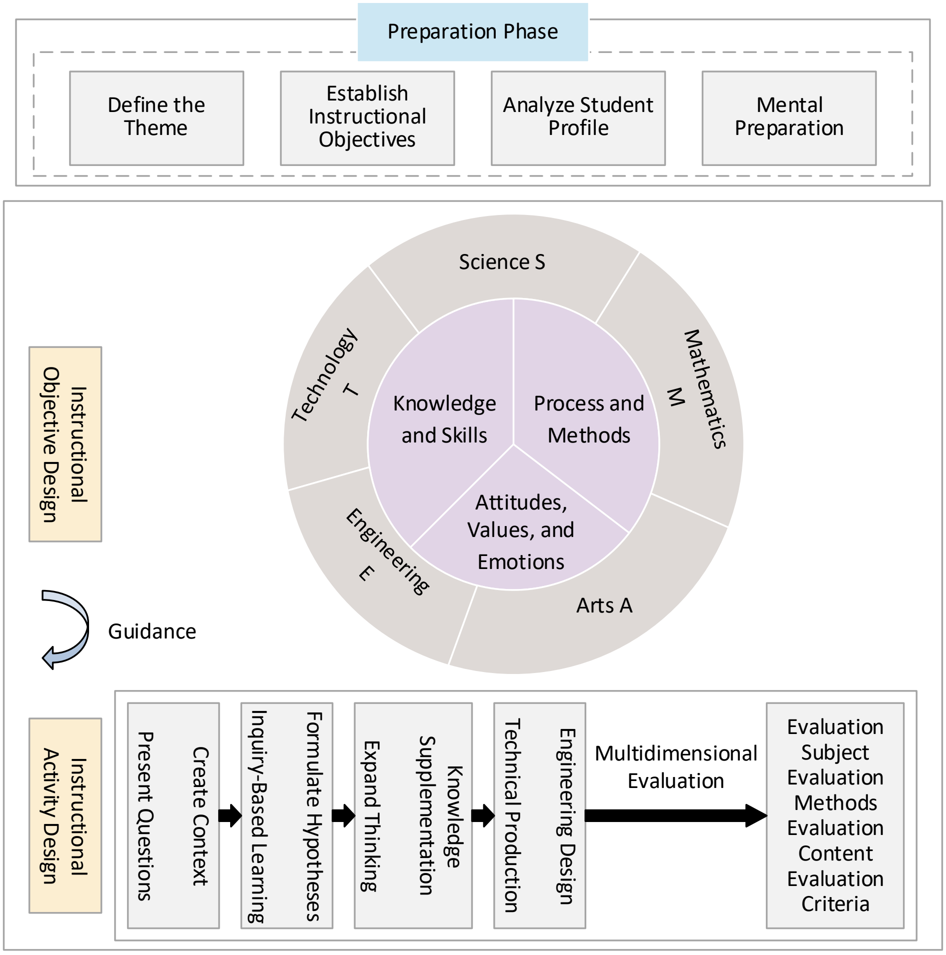


Figure 5: Interdisciplinary teaching model

(1) Determine the theme: With regard to the interdisciplinary education model oriented towards the integration of Chongqing folk music and Hongyan culture, the theme of the course must be linked to Hongyan culture, and it must be in line with the students' nearest development zone, even if the students are able to understand and produce learning effectiveness, and the most important thing is that the learners can effectively improve the sense of identification with the Hongyan culture, and promote the students' cognition of the Hongyan culture in the process of the course.

(2) Teaching objectives: Teaching objectives can be formulated by teachers according to each specific lesson, from the traditional three-dimensional objectives of teaching and the objectives of the content of the five areas of STEAM, in which the three-dimensional objectives of teaching are knowledge and skills, process and method, and affective attitude and values. The course objectives are the most specific teaching objectives, which are the basic basis for guiding the evaluation of teaching, and teachers can make adjustments according to the actual situation of teaching.

(3) Activity design: activity design is also known as the preparatory part before the class, before the course begins, the teacher carries out the teaching analysis, learning task design and the planning of the tools and materials used; the students will carry out the preview of the knowledge points, independently search for the materials related to the course content, and have a general understanding of the course content.

(4) Activity process: After clarifying the learning task, according to the teacher and the requirements of the task, students explore through group collaboration, share creativity and

ideas, propose and solve problems, engage in the collision of ideas, and develop an overall program for the project negotiation. Students in small groups as a unit, based on the program developed, the division of labor and cooperation in design and production of works, students as the main body, fully respect and play the role of the main body of the students and their own creativity, to complete the learning task together.

(5) Activity Evaluation: Activity evaluation is the stage of display evaluation, activity evaluation is a reflection and summary of the effect of the implementation of course learning. After the completion of the project, the activities are evaluated, the students present the results, and the teachers summarize the evaluation.

5 Conclusion

Through the empirical analysis of music majors from one Chongqing undergraduate university, four core indicators were identified, namely, professional skills, humanistic qualities, career development, and emotional values, with a cumulative percentage of variance explained of 66.125%, of which instrumental skills accounted for the most important part of the music learning ability of music majors, with a percentage of variance explained of 32.358%. Students' music learning ability was categorized into three types: better ability and good thinking, more ability and less planning, and lower ability and mediocrity. Except for the sub-dimension “internship experience”, the correlation of all the other ability indexes was significant at the 0.01 level. Based on the results of the study, we constructed a STEAM interdisciplinary teaching model for the integration of folk music and red rock culture in Chongqing.

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