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Article

Principal Component Analysis Methods and Teaching Reform Paths in Precision Teaching of Vocal Music Education in Colleges and Universities

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Abstract: In the exploration of the precise teaching reform of college vocal music, this paper takes the influencing factors of teachers as the research entry point. Aiming at the problems of the principal component analysis network, such as the inability to reflect the complete structural information of the data and the sensitivity to noise, the two-way two-dimensional principal component analysis is used as a filter, and the robust and non-greedy two-way two-dimensional principal component analysis network based on the L_1-paradigm distance metric is proposed, and then a principal component analysis network model is constructed. Meanwhile, in order to improve the robustness of principal component analysis, the MCD algorithm, which calculates the robust covariance matrix, is added to the model. Combined with the actual situation, a set of teacher influence factor indicator system containing 7 secondary indicators and 27 tertiary indicators is constructed from the three aspects of teachers' basic situation, teachers' classroom performance and teaching management. Applying the principal component analysis network model to the index system of teachers' influencing factors, the cumulative contribution rate of the six extracted index factors (teachers' situation, teaching attitude, teaching methods and means, teaching organization, system management, process management) has reached 83.61%, indicating that the six aspects are the main entry point for the precise reform of vocal music teaching.

Keywords: principal component analysis; MCD algorithm; vocal music teaching precision; teaching evaluation

1. Introduction

In the context of the new period, the importance of teaching innovation in vocal music education in colleges and universities is self-evident. With the acceleration of globalization and the rapid development of science and technology, the social demand for talents has changed from a single skill type to an innovative and complex type. Vocal art as an important carrier of human emotional expression and cultural heritage, its education and teaching innovation is not only related to the enhancement of individual artistic quality, but also the key to promote the prosperity of culture and art, and stimulate the vitality of social innovation [1-2]. Innovative vocal education can break the traditional constraints and provide students with a more open and diversified learning environment, which can help to stimulate students' creativity and imagination, encourage them to explore and try freely in the vast world of vocal art, and cultivate composite talents with both profound artistic skills and innovative thinking [3-5].

However, the ambiguous curriculum standards and lax curriculum at the present stage not only limit the comprehensive improvement of students' musical literacy, but also weaken their profound understanding and expression of music art [6]. Therefore, if colleges and universities want to cultivate composite talents with both solid singing skills and profound music theory, they need to optimize the curriculum of vocal education, strengthen the combination of theory and practice, broaden the disciplinary vision, and introduce diversified teaching methods [7-9]. Among them, the value of the precision teaching mode is to diagnose and feedback the teaching situation in time through the implementation of precision teaching, to provide a basis for teaching and learning, in order to improve the effectiveness of classroom teaching, and create a quality classroom [10]. Precision teaching is embodied in all aspects of classroom teaching, including the study of standards, system objectives, direction, quality and scientific assessment, each of which directly affects the effectiveness of classroom teaching and classroom quality [11-13]. Based on this, in college vocal music education, how to teach accurately has yet to be further explored and studied.

This paper firstly elaborates the core components of principal component analysis network method, as well as data dimensionality reduction and feature extraction process. On this basis, it proposes a two-dimensional principal component analysis network method and analyzes the mathematical expression of its objective function and its main advantages, and establishes a principal component analysis network model. Then the MCD algorithm is introduced and the operation steps are described in detail to help improve the robustness of the principal component analysis network model. At the same time, the index system of teachers' influencing factors is designed by taking into account the actual situation of vocal music teaching in colleges and universities. Subsequently, the proposed indicator system was subjected to PCA component analysis to calculate the correlation between indicators. The eigenvalues of the secondary and tertiary indicators are calculated and visualized to determine the components. Finally, combined with the analysis, the reform path of college vocal music teaching precision is proposed.

2. Principal Component Analysis Network Model

2.1. Construction of the Principal Component Analysis Network Model

2.1.1. Principal Component Analysis Network

First, block acquisition of images is performed in the input phase of the principal component analysis network (PCANet), with N training samples $x_i(i=1,2,\ldots,N)$ with dimensions $m\times n$. The sampling window size is $k_1\times k_2$ and satisfies $0<k_1\leq m$, $0<k_2\leq n$. The goal of PCA is to find a projection matrix W consisting of the first k principal components (PCs), and the PCA aims to maximize the subspace in the projection distances, which can be achieved by solving the following objective function equation (1):

$$\underset{W^TW=I_{k\times k}}{\arg\max}\sum_{i=1}^{N}\left\|W^TX_i\right\|_2^2\left(i=1,2,\ldots,N\right) \tag{1}$$

where $\|\cdot\|_2$ denotes the 2-parameter of the vector and has equation (2):

$$W=[v_1,v_2,\ldots,v_k]\in R^{m\times k} \tag{2}$$

The $I_{k\times k}\in R^{k\times k}$ represents the unit matrix.

For the i th sample x_i, the neighborhood blocks of all pixel points are extracted from this sample, and after vectorizing the image matrix, a new set of vectorized samples is obtained denoted as Equation (3):

$$X_i=[x_{i,1},x_{i,2},\ldots,x_{i,mn}]\in R^{k_1k_2\times\tilde{m}\tilde{n}}\left(\tilde{m}=m-k_1+1;\tilde{n}=n-k_2+1\right) \tag{3}$$

The above operation is repeated for the given N training samples, which are de-meaned for the sake of generality. The data matrix obtained after the treatment is equation (4):

$$X=\left[\overline{X}_1,\overline{X}_2,\overline{X}_3,\ldots,\overline{X}_N\right]\in R^{k_1k_2\times N\tilde{m}\tilde{n}} \tag{4}$$

With the PCA algorithm, the feature vectors of the data matrix X can be obtained and these feature vectors are converted into p filters in the first layer of the convolutional layer as in equation (5):

$$W_l^1=\underset{k_1,k_2}{mat}\left(q_l(XX^T)\right)\in R^{k_1k_2}\left(l=1,2,\cdots,p\right) \tag{5}$$

where $\underset{k_1,k_2}{mat}(v)$ denotes the transformation of the vector into the matrix $W \in R^{k_1 k_2}$ and $q_l(XX^T)$ represents the l th feature matrix of XX^T.

After zero-padding the training samples, these samples are used to perform convolution operation with W_l^1, and the output O_i^l is shown in Equation (6):

$$O_i^l = X_i * W_l^1 \left(i = 1,2,\cdots,N; l = 1,2,\cdots,p\right) \tag{6}$$

In the second layer of the convolutional layer, the number of training samples becomes $N \times p$ and q filters are chosen. The pixel blocks of all the training samples are collected, and in order not to lose the generality, it is also necessary to de-mean these pixel blocks, and the result of this layer is expressed as Eq. (7):

$$Q_{i,l}^k = O_i^l * W_k^2 \left(i = 1,2,\cdots,N; l = 1,2,\cdots,p; k = 1,2,\cdots,q\right) \tag{7}$$

The output layer of PCANet mainly contains binary hash coding and histogram statistics. The q output matrices $Q_{i,l}^k$ obtained in the second layer of the convolutional network are first binarized into a decimal coded image as Eq. (8):

$$\Gamma_i^l = \sum_{k=1}^{q} 2^{k-1} H\left(Q_{i,l}^k\right)\left(i = 1,2,\cdots,N; l = 1,2,\cdots,p; k = 1,2,\cdots,q\right) \tag{8}$$

where $H(\cdot)$ is the Hoviside step function, which is 1 when the pixel value is greater than zero and 0 otherwise, and each pixel value ranges from $[0, 2^q - 1]$. Then, all p processed data matrices Γ_i^l are divided into B regions while counting the histogram matrices of the decimals in each block with 2^q horizontal coordinates. And the B histograms are concatenated into a vector representation, denoted as $Bhist\left(\Gamma_i^l\right)$. Finally, the feature expression of the training sample x_i is encoded to obtain Eq. (9):

$$\begin{aligned} f_i &= \left[Bhist(\Gamma_i^1), Bhist(\Gamma_i^2), \ldots, Bhist(\Gamma_i^p)\right]^T \\ &\in R^{\left\langle 2^q \right\rangle pB} \left(i = 1,2,\cdots,N\right) \end{aligned} \tag{9}$$

The objective function of the PCANet algorithm uses F -paradigm squared as the distance measure. When there are outliers or noise in the sample, the computed projection matrix is easily affected. The spatial structure of the sample is destroyed when the pixel blocks are converted to column vectors. As a result, PCANet ignores some of the structural features of the image in its computation.

2.1.2. Two-Dimensional Principal Component Analysis Networks

The 2D Principal Component Analysis Network (2DPCANet) has the same architecture as PCANet, but it uses 2DPCA as a filter so that the dimensionality of the data matrix can be directly reduced. In 2DPCANet, the typical objective function is to use the F -paradigm square of the image reconstruction error, i.e., the error Eq. (10):

$$E_h = I_h - I_h W W^T \tag{10}$$

where h represents the index of the sample or image.

Then we have equation (11):

$$\underset{W^T W = I_{k\times k}}{\arg\min} \sum_{h=1}^{H} \left\|E_h\right\|_F^2 = \underset{W^T W = I_{k\times k}}{\arg\min} \sum_{h=1}^{H} \left\|I_h - I_h W W^T\right\|_F^2 \tag{11}$$

The main difference between 2DPCANet and PCANet is that PCANet has to convert the 2D matrix to 1D vector before calculating the feature vectors when using PCA to train the filter, while 2D2PCANet directly calculates the feature vectors of the so-called covariance matrix of the image without matrix-vector conversion when using 2D2PCA to train the filter, preserving the image's implicit spatial information in the image.The objective function of 2DPCANet is based on the square of the F -paradigm as in PCANet.

2.2. MCD Algorithm

The MCD algorithm is also commonly used to estimate the robust covariance matrix, the algorithm is still with the help of the Mars distance as a tool, through an iterative approach, to select the corresponding data covariance matrix determinant value of the smallest h samples one by one. On this basis, the final selected samples of the Mahalanobis distance as the weight, weighting calculation, to realize the original data robust covariance matrix estimation. The specific steps of the MCD algorithm are as follows:

In the first step, h samples are randomly selected from n rows p columns of the original data matrix equation (12):

$$X = (x_1, x_2, \cdots, x_n)^T \tag{12}$$

where h is taken in the range of $[0.5n, n]$, generally $h = 0.75n$, using these samples to form a subset H_1. Then calculate the sample mean vector t_1 and covariance matrix s_1 of the subset H_1, and use this calculation as the starting value of the algorithm as in equation (13):

$$t_1 = \frac{1}{h}\sum_{i\in H_1} x_i,\ s_1 = \frac{1}{h}\sum_{i\in H_1}(x_i - t_1)(x_i - t_1)^T\ (i = 1, 2, \cdots, h) \tag{13}$$

In the second step, based on the values of t_1 and s_1, the Mahalanobis distances of all the samples in the original data are calculated as in equation (14):

$$d_1 = \sqrt{(x_i - t_1)^T s_1^{-1}(x_i - t_1)}\ (i = 1, 2, \cdots, n) \tag{14}$$

In the third step, the h samples with the smallest sum of Mahalanobis distances are selected to form a subset H_2, and then the vector of sample means t_2 and covariance matrix s_2 of this subset are calculated as in equation (15):

$$t_2 = \frac{1}{h}\sum_{i\in H_2} x_i,\ s_2 = \frac{1}{h}\sum_{i\in H_2}(x_i - t_1)(x_i - t_1)^T\ (i = 1, 2, \cdots, h) \tag{15}$$

In the fourth step, based on the values of t_2 and s_2, the Mahalanobis distances of all the samples in the original data are calculated as in equation (16):

$$d_2 = \sqrt{(x_i - t_2)^T s_2^{-1}(x_i - t_2)}\ (i = 1, 2, \cdots, n) \tag{16}$$

In the fifth step, the third and fourth steps are repeated until $\det(s_k) = \det(s_{k-1})$ or $\det(s_k) = 0$, at which point the subset H_k is obtained. On this basis, the sample mean vector t_k and covariance matrix s_k of H_k are computed, and based on them, the Mahalanobis distances of all the original sample data are computed as in Equation (17):

$$d_k = \sqrt{(x_i - t_k)^T s_k^{-1}(x_i - t_k)}\ (i = 1, 2, \cdots, n) \tag{17}$$

where d_k approximately obeys a chi-square distribution with p degrees of freedom, from which a weight function with a confidence level of 0.975 is constructed as in equation (18):

$$w_i = \begin{cases} 0 & d_k > \sqrt{\chi^2_{0.975}} \\ 1 & d_k \le \sqrt{\chi^2_{0.975}} \end{cases}\ (i = 1, 2, \cdots, n) \tag{18}$$

In the sixth step, the sample mean vector t with covariance matrix s is computed for all the original sample data using $w_i(i=1,2,\cdots,n)$ as weights as in equation (19):

$$t=\frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i},\ s=\frac{\sum_{i=1}^{n} w_i (x_i-t)(x_i-t)^T}{\sum_{i=1}^{n} w_i -1} \tag{19}$$

At this point, the calculated t and s are the robust mean vector and robust covariance matrix estimated by the MCD method.

The MCD algorithm is highly accurate and robust, but because the algorithm is too complex in terms of computation and the computational efficiency is relatively low, it is not widely used in the early stage. The Fast-MCD algorithm, which appeared after this, solved the problem of computational complexity well and greatly promoted the application of the MCD algorithm.

3. Construction of a System of Indicators of Influencing Factors on the Part of Teachers

According to the availability of data, drawing on the research results of others, based on a combination of qualitative and quantitative analysis of the means of constructing the index system of influencing factors, the steps are:

(1) Constructing the hierarchical structure of the indicator system of teachers' influencing factors of teaching quality. The indicators are divided into the guideline level (first-level indicators), indicator level I (second-level indicators) and indicator level II (third-level indicators).

(2) Constructing the basic indicator set of influencing factors. Using the literature analysis method to analyze the existing research results, statistics and indicator reminders, summarizing the research results of others, and using the frequency statistics method, theoretical analysis method and expert analysis method to establish the general indicator set of the influence factors of teaching effectiveness.

(3) Using correlation analysis, coefficient of variation analysis and component analysis to set and screen the general indicator set for principal component and independence, so as to determine the required indicator system of teaching effectiveness influencing factors. Its main construction process is shown in Figure 1.

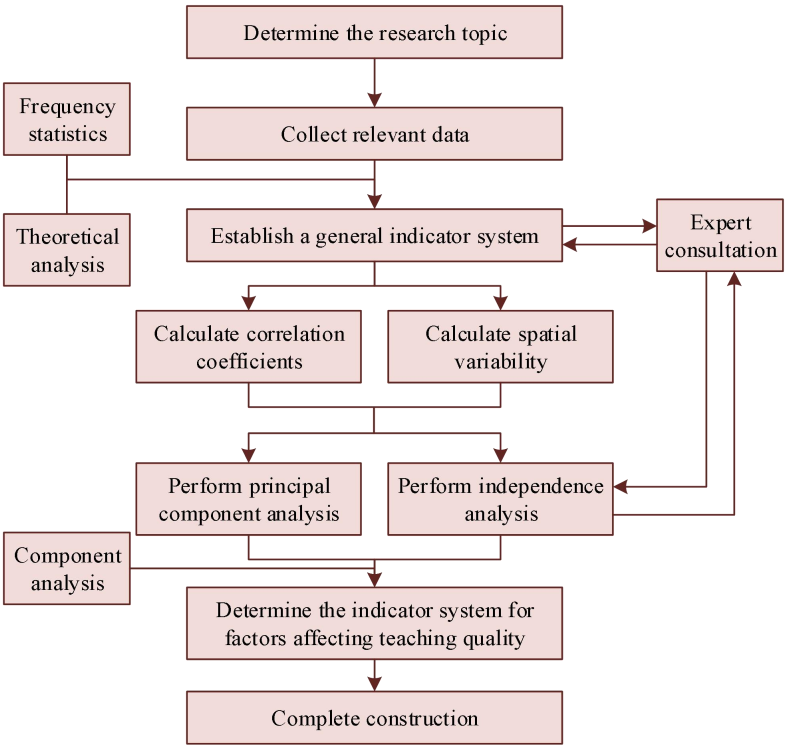

Figure 1. Index system of the build process.

Based on the above ideas, the indicators considered in the influence factors of vocal music teaching quality in colleges and universities in the influence factors of teachers' aspects mainly include 3 major level 1 indicators (teachers' basic situation, teachers' classroom performance, teaching management), 7 level 2 indicators (basic situation, teachers' level, teaching methods and means, teaching organization, system management, process management), and 27 level 3 indicators. The indicators of influencing factors on the teachers' side are shown in Table 1.

Table 1. The index system of influencing factors on teachers.

Primary index	Secondary index	Three-level index
(A) Basic information of the teacher	(A1) Basic information	(A11) Age and gender structure
		(A12) Educational background, degree and professional title structure
	(A2) Teacher level	(A21) Basic skills in education and teaching
		(A22) Professional theory and application level
	(A3) Teaching attitude	(A31) Competitive factors among teachers
		(A32) Teachers' lesson preparation status
		(A33) Teaching responsibility
		(A34) Handling of key points and difficulties
(B) Teacher's classroom performance	(B1) Teaching methods and means	(B11) Integrate theory with practice
		(B12) Suitability of teaching methods
		(B13) The application of modern innovative teaching methods
	(B2) Teaching organization	(B21) Assignment and inspection of vocal music homework
		(B22) Criticize and praise students
		(B23) Students' learning initiative
		(B24) Classroom interaction situation
		(B25) Class attendance rate and attendance rate
		(B26) classroom discipline
(C) Teaching Management	(C1) System management	(C11) Teacher training and improvement
		(C12) Whether teachers are engaged in scientific research administrative work
		(C13) web teaching evaluation system
		(C14) A scientific and reasonable assessment system
		(C15) The implementation of classroom teaching supervision
		(C16) Reward and punishment measures
		(C17) Distribution of class hour allowances
	(C2) Process Management	(C21) The selection situation of vocal music textbooks
		(C22) teaching load
		(C23) Class teaching scale

4. Application of the Model to the Indicator System

Based on the above established teacher aspects of influencing factors indicator system to develop teacher management quality questionnaire, to the M college voice major a total of 43 teachers and related management leadership method questionnaire, asked the respondents to the 7 secondary evaluation indicators, 27 tertiary indicators according to the degree of importance of the ratings, set a full score of 10 points. A total of 43 questionnaires were issued, 43 valid questionnaires were retrieved, and the validity rate of the questionnaire was 100%. The analysis of the quality indicators of school vocal teacher management is shown in Table 2.

Table 2. Score of management quality indicators for vocal music teachers.

Sample	Secondary index							
	A1	A2	A3	B1	B2	C1	C2	…
1	9	9	9	10	9	7	9	…
2	8	10	7	8	8	8	7	…
3	10	7	9	7	7	7	10	…
4	7	9	7	8	10	7	10	…
5	7	10	10	8	10	8	10	…
6	8	8	8	9	10	8	9	…
7	9	8	7	8	8	10	9	…
8	8	10	10	7	9	10	9	…
9	9	7	8	8	10	8	8	…
10	8	7	9	9	10	9	9	…
…	…	…	…	…	…	…	…	…

4.1. Processing of PCA Components of the Indicator System

Initially, the level 1 indicators:(A) teachers' basic situation and (C) teaching management were regarded as input indicators, and the level 1 indicator:(B) teachers' classroom performance was regarded as an output indicator.

Using the principal component analysis (PCA) of SPSS to analyze the performance of input indicators and output indicators related to the quality of vocal music teaching in the academic year 2019-2023 in M colleges and universities is shown in Table 3, and it is easier to make judgments and find out the reasons for the validity of the later decision-making units by discussing and summarizing the relevant contents through the support of the research data and the analysis plus the results of the empirical evidence. First of all, the use of KMO test and Barrlett's sphere test for the validity of the indicators, KMO test value range of 0-1, the larger the KMO value, the stronger the correlation between the variables.Barrlett's sphere test is used to test whether the variables are independent of each other, if Sig. < 0.05, indicating that the variables are correlated with each other, and can be subjected to principal component analysis. As shown in Table 3, the input indicator variables and output indicators Sig.=0.000 < 0.05, which can be subjected to principal component analysis.

Table 3. The variables KMO and Bartlett's sphericity test.

Variable	Year	KMO value	Sig.
Input variable	2019-2020	0.764	0.000
	2020-2021	0.832	0.000
	2021-2022	0.782	0.000
	2022-2023	0.801	0.000
Output variable	2019-2020	0.774	0.000
	2020-2021	0.811	0.000
	2021-2022	0.833	0.000
	2022-2023	0.899	0.000

4.2. Assessment of Vocal Teaching Based on Principal Component Analysis

4.2.1. Interpretation of Variance

The correlation matrix R was calculated for a total of 34 indicators, and the eigenvalues and eigenvectors were calculated and arranged in ascending order of the eigenvalues to obtain Table 4. 15 eigenvalues are listed in the table, and each eigenvalue corresponds to one component. As can be seen from Table 4, the cumulative variance of the first six indicator factors amounted to 97.522%.

Table 4. The total variance of the explanation.

Serial Number	Initial eigenvalue			Extract the sum of squares and load			Rotate the sum of squares for loading		
	Total	Variance(%)	Accumulate (%)	Total	Variance(%)	Accumulate (%)	Total	Variance(%)	Accumulate (%)
1	9.911	74.365	74.365	9.911	74.365	74.365	2.618	24.669	24.669
2	6.381	12.699	87.064	6.381	12.699	87.064	1.889	23.202	47.871

3	5.571	5.72	92.784	5.571	5.72	92.784	1.81	22.696	70.567
4	2.104	2.1	94.884	2.104	2.1	94.884	1.675	15.793	86.36
5	1.062	1.52	96.404	1.062	1.52	96.404	1.425	8.232	94.592
6	1.027	1.118	97.522	1.027	1.118	97.522	0.28	2.96	97.552
7	0.86	0.853	98.375						
8	0.732	0.678	99.053						
9	0.638	0.28	99.333						
10	0.536	0.185	99.518						
11	0.516	0.179	99.697						
12	0.48	0.137	99.834						
13	0.431	0.085	99.919						
14	0.281	0.051	99.97						
15	0.017	0.03	100						

4.2.2. Component Eigenvalue Visualization

The visualization of component eigenvalues is shown in Figure 2, where the horizontal coordinate represents the “component number” and the vertical coordinate represents the “component eigenvalue”, which reflects the importance of each component. From the figure, it can be seen that the six principal components on the left already contain most of the information of the original variable, so it is more reasonable to take six principal components to represent the original variable.

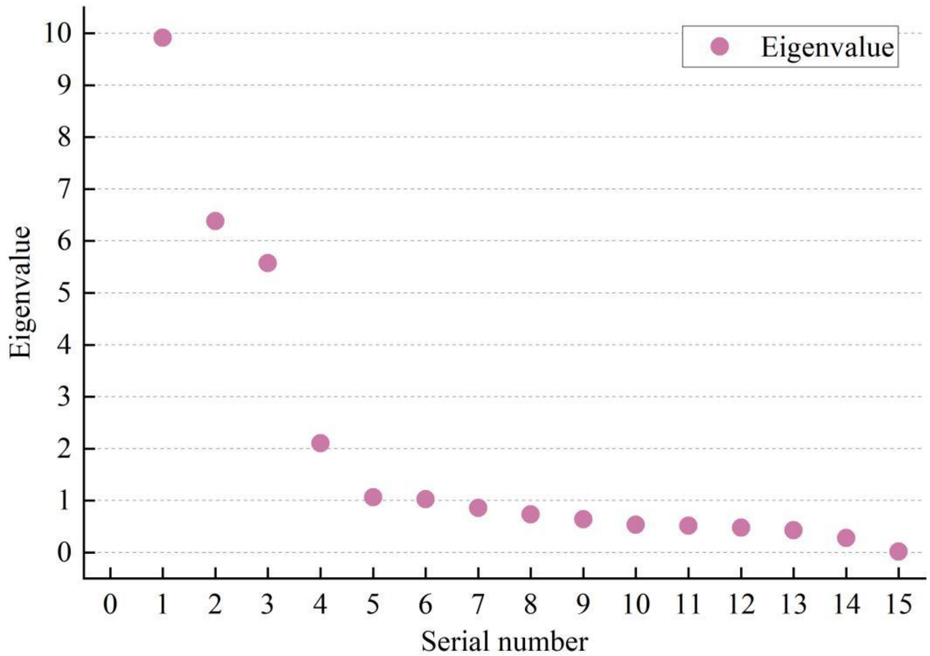

Figure 2. Visualization of component characteristic values.

4.2.3. Commonality of Variables

After determining the selection of six components (teacher situation, teaching attitude, teaching methods and means, teaching organization, system management, process management), the “common factor variance” is calculated as shown in Table 5, which gives the common degree of the initial secondary variables, and the “Initial” column is 1, representing that the information content of the original secondary variables is 100%, and the “Extracted” column is the value of the common degree of the secondary variables. For example, the extracted value of (A1) teachers' situation is 0.868, which can be interpreted as 86.8% of the information extracted from (A1) teachers' situation. The most extracted amount is 99.00% for (B1) Teaching Methods and Approaches. In general, it can be seen that the six components contain the vast majority of the amount of information.

Table 5. Common factor variance.

	Initial	Extract
(A1) Teacher situation	1.000	0.868
(A3) Teaching attitude	1.000	0.958
(B1) Teaching methods and means	1.000	0.99
(B2) Teaching organization	1.000	0.927
(C1) System management	1.000	0.928
(C2) Process Management	1.000	0.895

4.2.4. Contribution Rate

The eigenvalues, contribution rates and cumulative contribution rates of the correlation coefficient matrix of the standardized original data are shown in Table 6, where the larger the cumulative contribution rate is, the less data information is lost, i.e., the more information of the original indicators can be covered. As can be seen from Table 6, the cumulative contribution rate of the first six indicators has reached 83.61%, indicating that the six factors (teacher's situation, teaching attitude, teaching methods and means, teaching organization, system management, process management) basically represent the information of 34 indicators.

Table 6. Eigenvalues, contribution rates and cumulative contribution rates.

Principal component	Index	Eigenvalue	Rate of contribution(%)	Cumulative contribution rate (%)
1	(A1)	9.911	11.46	11.46
2	(A3)	6.381	11.28	22.74
3	(B1)	5.571	17.79	40.53
4	(B2)	2.104	16.85	57.38
5	(C1)	1.062	13.25	70.63
6	(C2)	1.027	12.98	83.61
7	(A2)	0.998	2.2899	87.7729
8	(A11)	0.931	1.873	87.7729
9	(A12)	0.746	1.23	89.0029
10	(A21)	0.727	0.9867	89.9896
11	(A22)	0.322	0.9698	90.9594
12	(A31)	0.19	0.7051	91.6645
13	(A32)	0.566	0.7026	92.3671
14	(A33)	0.325	0.6787	93.0458
15	(A34)	0.505	0.6611	93.7069
16	(B11)	0.315	0.5521	94.259
17	(B12)	0.32	0.5482	94.8072
18	(B13)	0.578	0.5476	95.3548
19	(B21)	0.903	0.5446	95.8994
20	(B22)	0.095	0.5252	96.4246
21	(B23)	0.543	0.4678	96.8924
22	(B24)	0.594	0.4325	97.3249
23	(B25)	0.02	0.4166	97.7415
24	(B26)	0.643	0.4115	98.153
25	(C11)	0.448	0.2957	98.4487
26	(C12)	0.62	0.2756	98.7243
27	(C13)	0.256	0.2623	98.9866
28	(C14)	0.589	0.2161	99.2027
29	(C15)	0.297	0.1627	99.3654
30	(C16)	0.985	0.1579	99.5233
31	(C17)	0.606	0.143	99.6663
32	(C21)	0.553	0.138	99.8043
33	(C22)	0.766	0.1003	99.9046
34	(C23)	0.326	0.0954	100

4.3. Reform Path of Accuracy of Vocal Music Education in Colleges and Universities

Combined with the above analysis, it can be seen that the important main body of the precision reform of college vocal education is the teacher and professional teaching management. At present, the implementation of teaching precision reform cannot be separated from the assistance of artificial intelligence technology, so artificial intelligence technology is chosen as the means of implementation of precision reform. This section is based on the perspective of teachers and professional teaching management, and puts forward the following precise reform path:

(1) As the leading teacher in the classroom and even in the overall teaching, college vocal teachers need to keep improving and perfecting their teaching methods and means, but also need to be open-minded and actively explore the teaching mode under the artificial intelligence technology. In the above analysis, the contribution rate of "teaching methods and means" to the quality effect of precise teaching of vocal music is as high as 16.85%, and its importance in the teaching of vocal music is self-evident. Therefore, in the use of artificial intelligence technology, vocal teachers should focus on the innovation of teaching methods and means. Make full use of artificial intelligence technology to analyze the characteristics of students' learning behavior, expand corresponding learning resources, and formulate personalized training programs according to the characteristics of different students. By giving full play to students' individual strengths and specialties, precise teaching is carried out to actively promote the improvement of the overall quality of vocal music teaching.

(2) Professional teaching management determines the direction, content and mode of professional vocal music teaching. The professional teaching management of vocal music not only needs to firmly control the basic situation of teachers, classroom performance and teaching management, but also needs to closely follow the development trend of the times and introduce and encourage the development of artificial intelligence technology-assisted teaching. In the process of artificial intelligence technology-assisted teaching, it is also necessary to establish and improve the corresponding teaching framework, as well as the relevant management system. On the whole, professional teaching management should serve as the leader and escort of the precise reform.

5. Conclusion

This paper takes the principal component analysis method as a research tool, takes the influencing factors of teachers as the entry point, and proposes that teachers should focus on the innovation of teaching methods and means, and the professional teaching management should focus on the precise reform path of vocal education in colleges and universities based on the development of teaching mode by artificial intelligence technology.

In the principal component analysis method, this paper combines the two-dimensional component analysis network and MCD algorithm to build a principal component analysis network model. The model effectively reduces the influence of outliers on the model performance by using L_1 paradigm as the distance metric. And the MCD algorithm in robust principal component analysis is used to calculate the robust covariance matrix to improve the robustness of the model.

In terms of the influencing factors on the teachers' side, this paper establishes an indicator system consisting of 6 secondary indicators and 27 tertiary indicators from the three levels of teachers' basic situation, teachers' classroom performance and teaching management. In the analysis based on the principal component analysis network model, the cumulative variance of the six factors (teacher situation, teaching attitude, teaching methods and means, teaching organization, system management, process management) reaches 97.522%, and the cumulative contribution rate reaches 83.61%.

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