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Retraction

Retracted: Evaluation Method of Vocal Music Teaching Quality for Music Majors Based on the Theory of Multiple Intelligences

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] D. Li, "Evaluation Method of Vocal Music Teaching Quality for Music Majors Based on the Theory of Multiple Intelligences," *Mathematical Problems in Engineering*, vol. 2022, Article ID 3353776, 11 pages, 2022.

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Research Article

Evaluation Method of Vocal Music Teaching Quality for Music Majors Based on the Theory of Multiple Intelligences

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The quality evaluation of vocal music teaching for music majors is of great significance to music education. Based on the theory of multiple intelligences, this paper constructs a model for evaluating the quality of vocal music teaching for music majors and introduces the theory of multiple intelligences into the operation form, design requirements, and recommended lesson examples of music teaching unit design. The experimental data and questionnaire data collected by the model verify that this operation is beneficial to the improvement of students' music listening scores, vocal music comprehension scores, and total scores and solves the quantitative problem of vocal music teaching quality evaluation. In the simulation process, the engineering testing and analysis method uses the correlation rate and correlation strength as the analysis indicators, comparing the platforms for the quality evaluation of vocal music teaching in music majors and the corresponding quality evaluation data preprocessing process. The experimental results show that the algorithm performance evaluation is carried out based on the three aspects of quality evaluation association rules, algorithm running time, and algorithm memory consumption. The multiple intelligence algorithm is applied to vocal music teaching analysis of association rules for quality evaluation: when 4000 tasks call for 20–40 virtual resources, the total time spent is reduced by 61.7%, which has a significant positive effect on the knowledge expansion and ability improvement of music majors.

1. Introduction

The introduction of multiple intelligence perspectives in the unit teaching design of music conforms to the requirements of the new music curriculum standards, which can not only provide students with more opportunities and directions to participating in music learning [1] but also provide students with more perspectives to design and organize teaching. The introduction of foreign advanced theories into regional educational practice has always been a general trend [2], and how to operate and verify its specific impact and role in the process of introduction is of great significance [3–5].

At present, most of the papers involving quantitative research involving the application of multiple intelligences theory to teaching start with the measurement of multiple intelligences and then design experiments to verify the validity of the theory [6]. The experimental results include improving the multiple intelligences of the data [7]. Action research is used in some papers [8], and it is more inclined to cautious attitude [9–11]. Multiple Intelligences Theory is a very good perspective for organizational education, but it is not necessarily an educational purpose [12]. Both knowledge and technology are students' learning content, and the flexible and effective use of knowledge and technology is an important learning goal for students [13]. This theory urges educators to better understand and pay attention to the individual differences of students, and promote education through more perspectives and strategies [14]. The introduction of music teaching will definitely reform some of the stereotyped status quo in education and teaching [15–17]. The research of Devaney [18] is conducive to enriching students' music learning experience, improving their comprehensive musical literacy, and having the opportunity to access more ways to achieve learning and improve their enthusiasm for learning. Jiang [19] created various scales to measure multiple intelligences. Li [20]'s work has greatly enriched scholars' and students' understanding of students' intelligence performance. In the introduction process of the previous research papers on the guidance of multiple intelligences theory in teaching practice, Magraner [21] first designed a selection intelligence scale, mastered students' dominant intelligence, and designed teaching according to their dominant intelligence. Subsequent tests of the effectiveness of the teaching experiments included improvements in the Student Intelligence Scale data [22]. This operation is not endorsed by the proponents of the theory. What is more respected is to record the performance of students in various aspects of multiple intelligences, and to issue students' development reports based on the records [23].

This paper takes music students and music teaching as the research entry point and constructs a quality evaluation model of vocal music teaching for music majors. The first is to determine whether it is feasible or feasible to introduce the theory of multiple intelligences into the specific teaching practice of music. If you have any requirements, give a recommended lesson design; then, through the design and implementation of teaching experiments, verify whether the music unit teaching design is meaningful in the perspective of multiple intelligences from the perspective of students, and the challenges encountered in the design of music unit teaching from the perspective of multiple intelligences theory and the enlightenment of this operation to teaching.

2. Theoretical Analysis of Multiple Intelligences

2.1. Multiple Intelligence Levels. The multiple intelligence module mainly realizes the following functions, user management and authority management. In cloud technology, GCE resources are divided into two parts with fundamentally different potentials-server and client. The user management module is mainly used by the system administrator to manage the basic information of users, including adding user information, removing user information, and modifying user information $a(i)$, as well as assigning permissions to users. When the "Add User" button $1 - a(n)$ is clicked, the btnListAdd Click() event will be triggered, and an additional page for managing users will pop up on the main interface, where the system administrator can add the user's basic information $s(t) + v(t)$. After the administrator fills in the information, click the "Add" button, trigger the btnAdd Click() event, and call the Proc GetUserInfo stored procedure to add the users.

$$\sum_{i,j<t} a(i) - a(i-1) - \sum \frac{1 - a(n)}{a(n-1)} = \frac{1}{A'}, \frac{s(t) + v(t)}{ds} - \frac{s(t) - v(t)}{ds} = 0. \tag{1}$$

In the first principal component $g(a,b)$, the coefficients of each index variable are close, the values are not much different, and the load $\exp(a)$ is close. We call the first principal component the comprehensive intelligence factor $v(b)/v(r)$. This principal component can be regarded as an evaluation of students' learning effects. It can be seen that the contribution rate of the principal component to the overall is the largest (33.125%), indicating that the principal component has a strong ability to comprehensively index $v(a+b)/v(r)$.

$$\min g(a,b) = \begin{cases} 1 - \exp\left(1 - \left(\dfrac{a}{2\,d}\right)\right) \\ \\ 1 - \exp\left(\dfrac{1-b}{2a}\right) \end{cases}, \tag{2}$$

$$G(a,b,r) = \frac{\sum_{i,j<p} v(a) + (v(b)/v(r))}{\sum_{i,j<p} v(a+b)/v(r)}.$$

This refers to a set of values used to distinguish the relative importance of each indicator in the indicator system and to characterize the relationship between the indicators, revealing the difference in the impact value of the corresponding factors on the indicator system. The determination of the weight is an important factor to ensure the scientific and accurate evaluation system, and the weight has a strong guiding function. When determining the weights, the integrity of the weights $d(a)$ (the value of each indicator in the system and its contribution to the system), objectivity $1 - n$ (the actual status of the indicator in the system), and space-time $p(a, b)$ (the certainty and variability of the weights) should be considered.

$$\frac{\sum_{i,j<p} d(a) + d(b) - d(c)}{1 - n} < 1 - a,$$
$$\sum_{i,j<p} \frac{k(a/i + b/i)}{k(r)} < 1 < \sum p(a,b) - k(i)k(j). \tag{3}$$

The multiple intelligence evaluation index system is a complex multi-factor system with many evaluation indexes and each index is an indispensable aspect of the evaluation elements, but the influence of each index $k(i)$ on the evaluation system is not equal. Therefore, it is necessary to distinguish the contribution of each index to the overall quality of the evaluation by setting weights. Grid and cloud technologies provide users with problem-oriented algorithmic services that use only a fraction of the overall computing potential of GCE, which cannot meet the need to scale large-scale processing systems for exponentially growing traffic and globally distributed amount of information.

There are many ways to determine the weights of the indicators. Due to the difference between the evaluation objects $v(x,y)$ and the survey objects, there are certain limitations. This paper adopts the Delphi method to determine the weight coefficients $w(x,y)$ of each evaluation index $g(x,y)$.

$$v(x,y) = [c + w(i + v * j)] * w(x)w(y),$$
$$g(x,y) = \frac{[g(a) - g(b)]}{g(x,y)} - \frac{[g(i) + g(j)]}{1 - g(x,y)}. \tag{4}$$

The distribution of the support degree of the quality evaluation data is presented as "tailing index distribution," and the darker the color, the greater the support degree value of the quality evaluation item. Some of the popular exact algorithms use exact enumeration, implicit enumeration, branch and bound, cut plane, and dynamic programming. Figure 1 performs logarithmic operation on the maximum support degree of the entire quality evaluation data to obtain m, and then divides it into n intervals on average to form a stepped distribution of the target data area.

Unit instructional design means that students, as instructional designers, start from the perspective of a chapter, theme, or unit, make comprehensive use of various teaching strategies and teaching forms, and carry out a reasonable period of time according to the needs of a reasonable amount of knowledge, organizational systems, and learners' needs for effective learning (not limited to one class hour) teaching plan, allowing learners to complete the learning of a relatively complete unit of knowledge or experience in certain steps to achieve preset goals. All students can get task evaluation points, for example, +5 points for completing each random check, and 15 points for not completing each test; the actual score of each test is converted into process evaluation points as follows: more than 80 points will be divided into +20 points, 60–79 points are rated as +15 points, 40–59 points are rated as +10 points, and below 40 points are rated as +5 points.

2.2. Vocal Teaching Test. Through the evaluation of the 8 items of vocal music teaching, students' ability to solve practical problems can be observed from many aspects of students' participation in teaching activities, which can not only reflect the development level of students' intelligence but also judge the students by measuring students' data in real situations. To further evaluate the process of students' intelligence development, the author expounds on the hierarchical teaching system of the basic multiple intelligences theory from five aspects: evaluation principle $x(i)$, evaluation standard $x(i-1)$, evaluation example $y(i)$, evaluation effect $y(i-1)$, and evaluation reflection $1-i$. Ask students to identify the image, and then describe it; ask students to imagine the corresponding process description to form an image, make process diagrams and diagrams, and then describe it: through the students' vision. A motion cannot be implemented in the current iteration as long as it is in the taboo list, so revisiting the algorithm can be avoided since it visited the solution during the last few iterations, which helps prevent the algorithm from converging to a local optimum.

$$\begin{aligned}&\left(\frac{\sum_{i,j<p}\sqrt{x(i)+x(i-1)}-i}{1-i}\right)<1-\sum 1-y(i),\\&\left(\frac{\sum_{i,j<p}x(i)-y(i)-i/1-i}{1-i}\right)=1-\sum\frac{1-y(i)}{1-i}.\end{aligned}\tag{5}$$

After the compression function $x(i)\ -y(i)$, the data area is divided into 10 "equal-width" areas. If there are no data points in some "equal-width" areas, the number of "equal-width" areas will be reduced to 9, and so on there are data points in the "equal width" area. For example: after the compression function, the data area $v(i,k)$ is divided into 5 areas A, B, C, D, E, but there is no data point in the area D, then the "equal width" is recompressed to form 4 areas A, B, C, D, and the 4 areas all contain data points $w(a,b)$, then the area division $v(i,j)$ ends.

$$v(i,k)=\left\{1-\frac{1}{m-1}\sum_{i,j<p}v(i,j)\frac{1}{m}\sum_{i,j<p}\frac{v(i,j)}{v(k)},w(a,b)=1-w(1-a)-w(1-b).\right.\tag{6}$$

In order to improve the adaptability $w(1-a)$ of the algorithm to unknown data, the support value of each item is used as an independent variable, and its logarithmic value is used as the standard for dividing the "equal width" area. Compared with the method of averaging the difference between the maximum support degree and the minimum support degree $v(i)/d(i)$.

$$\begin{aligned}&d(i,j)=\operatorname{sig}\operatorname{mod}(i-j),\text{for}\left\{\frac{v(i)}{d(i)}-d(j)\right\},\\&1-\sum\frac{1-r(i)r(n)}{1-r}-\sum\frac{1-d(i)d(n)}{1-d}\subseteq C(r,d).\end{aligned}\tag{7}$$

Research on association rule mining algorithm for vocal music teaching quality evaluation $r(i)r(n)$ based on swarm intelligence will integrate swarm intelligence into association rule mining method $1-d$, and realize the application and extension $C(r,d)$ of swarm intelligence theory to engineering practice. To further analyze the characteristic laws of their respective algorithms, the association rule mining parameters are configured the same (the minimum support is 0.01, and the minimum confidence is 0.05), and the parameters of the A1 algorithm, A3 algorithm, and A2 algorithm are configured to the same scale and magnitude (the number of units in the A1 algorithm is 40, the number in the A3 algorithm is 40, the number of probes in the A2 algorithm is 20, and the attack range is 9), Table 1 has iterations from 100 to 400 with an interval of 100.

Referring to the above for the computer hardware platform of the test experiment, continuously extract 12-week quality evaluation data through the network management system, and divide it into three groups. The first set of data is used as engineering training data, and the remaining two sets of data are used as engineering test data. The first group of quality evaluation data was intercepted according to the time window of 2 seconds and the sliding window of 1 second. There are two general types of barriers: static barriers and dynamic barriers. The obstacle is static if it

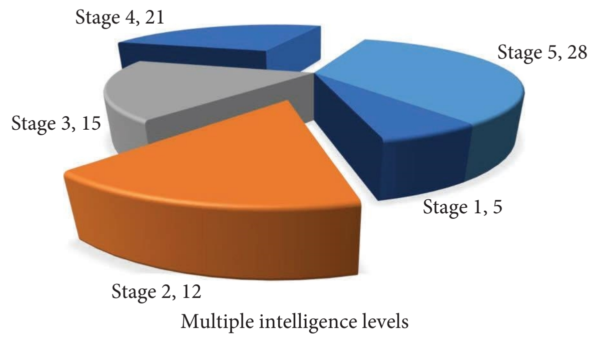

Figure 1: Multiple intelligences data region hierarchy.

Table 1: Vocal teaching test.

Vocal unit	Interval	Standard deviation	Mean value	Mean square error
Range 1	100	0.13	0.38	0.29
Range 2	200	0.01	0.30	0.06
Range 3	300	0.86	0.29	0.35
Range 4	400	0.43	0.24	0.24
Range 5	500	0.49	0.27	0.03
Range 6	600	0.97	0.59	0.13

does not change form and position for a period of time; otherwise, the obstacle is dynamic.

Combined with the network quality evaluation data, the performance test (the relationship between node size, iteration times, and the number of association rules, the relationship between the distribution of node types and the total number of association rules, the performance comparison between A2 and Apriori algorithm) and engineering test (association rate, association strength), the application of A2 algorithm in process thinking and engineering shows the characteristics of global optimization and low resource consumption of swarm intelligence method.

2.3. Quality Evaluation Clustering. The evaluation method and evaluation standard of the intelligent model is not only an important part of measuring the quality of the algorithm but also provide an effective way of metric analysis. To evaluate the overall performance of the swarm intelligence association rule mining algorithms, the above algorithm performance indicators and engineering indicators are quantitatively evaluated at equal intervals.

The maximum value and the minimum value in the two most values are equally divided into four areas, which are assigned as 1, 2, 3, and 4, respectively. For example: under the condition that the number of iterations is 300, the running time of the A1 algorithm, A3 algorithm, and A2 algorithm is 18 s, 4s, and 29 s, respectively, the maximum value is 29 s, the minimum value is 4s, Table 2 divides it into four equally spaced regions (4, 10.25, 16.5, 22.75, and 29) and assigns the values to 4, 3, 2, and 1; in turn, then the corresponding evaluation values of the A1 algorithm, A3 algorithm, and A2 algorithm are 2, 4, and 1.

This module is mainly to complete the customization of students' teaching evaluation indicators and the maintenance of the indicator library. The administrator selects the indicators to customize the evaluation model, enters the model name for the evaluation model, and stores it in the indicator library for easy selection. The administrator can add or delete indicators for the existing models in the model library as required to achieve the desired effect. Customizing the different evaluation models, it can meet the evaluation needs of different teaching. In the swarm intelligence association rule mining algorithms, the association rate can reach more than 60% under the same parameter configuration. The resulting cluster from this case will also include the arrangement of nodes. Thus, we can see whatever route the salespeople themselves take as a cluster, and the total number of salespeople represents the number of clusters that will be generated.

Under the condition that the number of iterations is 100, the A1 algorithm and the A3 algorithm have a relatively small number of association rules obtained by mining, resulting in a higher association rate. However, when the number of iterations is greater than 100, the association rates of the swarm intelligence association rule mining algorithms are improved and tend to be stable, and the association rate of the A2 algorithm is relatively stable. It is not difficult to see from the above table that the intelligence of students is diverse, the various intelligence development levels of each student are not balanced, the intelligence strengths of each student are also different, and the intelligence distribution of students is presented in the form of a spectrum.

Among all 40 intelligence-related descriptions, Figure 2 reflects that their intelligence development is good, 26 of them exceed 50%, and the remaining 14 reflect that the students' intelligence development lags by more than 50%. The original sequence data was symmetrically extended forward by 12 units and backward by 13 units. Analysis of Matlab wavelet decomposition results: where S is the original data signal, S can be a complex subsequence composed of different frequency components, including five high-frequency $d1$, $d2$, $d3$, $d4$, $d5$, and low-frequency $a5$, low-frequency $a5$ fully reflects the evaluation. There is a simple linear correlation between total addition and subtraction; the second is a possible curve trend; the third is a positive and negative correlation; the fourth is an obvious functional relationship.

The main change trend of the index throughout the year shows three peaks throughout the year, and the evaluation index value alternates many times in turn, indicating that the quality of vocal music teaching fluctuates greatly throughout the year, and other high-frequency signals do not explain the original data signals. In terms of performance indicators, the A3 algorithm is slightly better than the A2 algorithm, and the overall performance comprehensive evaluation index of the above two algorithms is twice that of the A1 algorithm; in terms of engineering indicators, the overall engineering comprehensive evaluation index of the A2 algorithm is better than the other two algorithms, A3 algorithm is close to the comprehensive evaluation index of A1 algorithm engineering.

Table 2: Characteristic index algorithm.

Evaluation method tests	Index algorithm codes
The evaluation method evaluation	#include #include #include #include
The swarm intelligence $1 - r$	#include #define rand_01
An effective way of	Const int numofdims = 30;
Indicators are evaluated	Const int numofparticles = 50;
The quality of the algorithm $v(i, j)$	Using namespace std;
Association rule	//typedef void (*fitnessfunc)
The overall performance of $1 - d$	Voidfitnessfunc(float, x[numofparticles]
The above algorithm $1 - d(i)d(n)$	Float fitnesses[numofparticles])
At equal intervals	(float x [numofdims];
Mining algorithms $i + x(i)$	[numofparticles]
Metric analysis $x(1 - i)$	(float)rand()
To evaluate $k(i)k(j)$	Memset(fitnesses, 0);
Performance indicators engineering	For(int $i = 0$; $i <$ numofparticles; i++)
The intelligent model not only a/i	Sizeof (float)*numofparticles

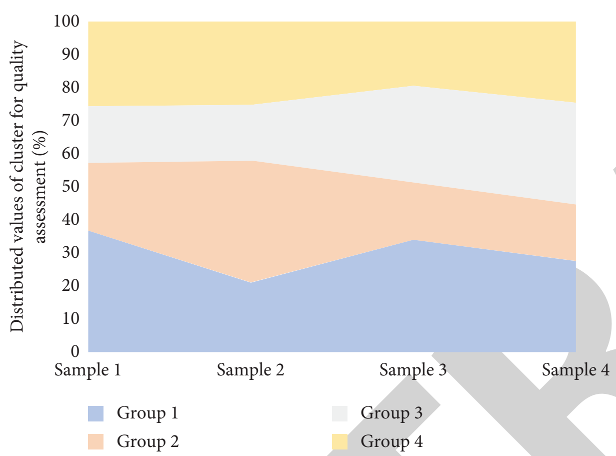

Figure 2: Quality evaluation clustering intelligence distribution.

3. Construction of the Evaluation Model of Vocal Music Teaching Quality

3.1. Multiple Intelligence Unit Nesting. The 4-week data in the vocal music teaching quality evaluation data of the continuous multiple intelligence unit is used as the first group of "training data," the quality evaluation association rules contained in it are mined through the A1 algorithm, and the data of the last 4 weeks is used as the second group of "test data."

Specific method: intercept the full quality evaluation according to the fixed flow time window, and include all non-itemsets into the quality evaluation correlation rate and correlation strength calculation (the itemsets themselves do not correlate; the test situation is as follows). Under the condition of constant confidence, the time-consuming of the A1 algorithm increases as the number of iterations increases, but the number of rules obtained increases significantly; compared with the Apriori algorithm, the efficiency of the A1 algorithm is significantly higher, for example, the number of iterations is 120, the time-consuming of the algorithm is only 17% of that of the Apriori algorithm, but the number of rules obtained in Figure 3 accounts for 88% of the total number of rules.

The results of the questionnaire survey conducted at the end of a semester of the teaching experiment showed that the differences in the self-assigned scores of the experimental class and the control class in the five survey directions became more obvious than at the beginning of the term. After the experimental class went through the teaching experiment, the students' cross-cultural communication enthusiasm and self-confidence were higher than the feedback given by the control class, with an increase of 5.24 points, accounting for 35% of the full score in the survey direction.

The experimental classes were also assigned higher scores in other survey directions. The higher range from high to lowest was self-evaluation in class (4.68 points, accounting for 18.7% of the full score for this survey direction), enthusiasm for classroom learning (3.82 points, accounting for the full score of this category), enthusiasm and self-confidence in cross-cultural communication (3.6 points, accounting for 24% of the full score), and enthusiasm for completing homework (2.58 points, accounting for 17.2% of the full score). Judging from the difference in assigned points and the proportion of the increase in assigned points to the full score of each survey direction, after a semester of teaching experiments, the experimental class was compared with the control class, and the difference in the scores of after-school homework completion and classroom learning enthusiasm was in five survey directions. This may be partly attributable to the fact that both classes had the same music student and received little difference in teaching styles.

3.2. Vocal Teaching Structure. For each vocal music teaching description, five criteria for students' self-identification are given: (A) Completely in line with my actual situation, (B) In line with my actual situation, (C) Basically in line with my actual situation, (D) Does not conform to my actual situation, and (E) It does not match my actual situation at all. In the first stage, an unsupervised learning data clustering method is used to locate the center of the cluster without using class information, and in the second stage, the class information is used to improve the location of the cluster center, thereby reducing the number of misjudged cases.

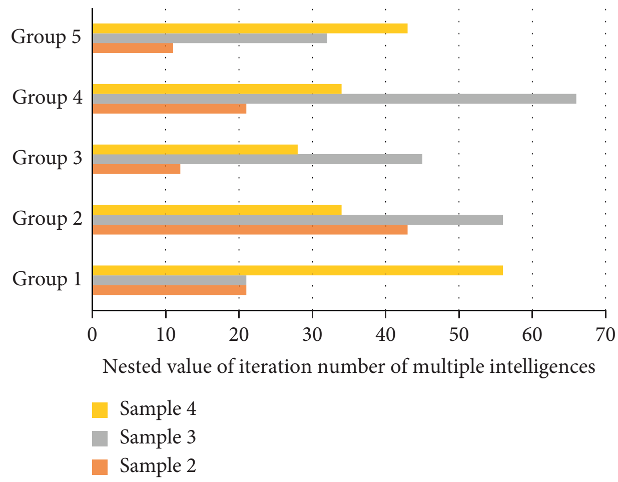

FIGURE 3: Multiple intelligence iterations nesting.

Before obtaining clusters, their classes must be represented. Moving to two-stage supervised learning, labeling is done by voting (if most of the data in the cluster belong to the class, a so-called cluster is labeled as the class). In the second stage of supervised learning, if it belongs to the same class, then move towards it, otherwise, it will move away. If it is greater than 5% of the selected significance level, the null hypothesis is accepted, indicating that there is a nonsignificant correlation between the two variables.

Before the teaching experiment, the average scores of the students in the two classes were similar in the five survey directions. After one semester, the data in Figure 4 shows the average scores of the surveyed students in the questionnaire, their enthusiasm for learning in class, self-evaluation in class, enthusiasm for completing homework, enthusiasm for cross-cultural communication and self-confidence, and their enthusiasm for future careers. Expectations and the other five survey directions have increased in both classes but at different rates. It can be seen intuitively that, compared with the control class, the students in the experimental class have significantly higher scores in the four survey directions: enthusiasm for classroom learning, self-evaluation in class, expectations for future careers, and enthusiasm and confidence in cross-cultural communication.

In terms of enthusiasm for homework, although the feedback scores of the two classes have improved, the difference is not as obvious as that of the other four survey directions. It can be said that this investigation direction is least affected by this teaching experiment. It mainly includes two modules, price form filling and evaluation form submission. According to the different vocal music teaching projects researched by different students, fill in the vocal music teaching evaluation form of each student, in turn, input relevant data, and information, or select one or more of them to fill out.

3.3. Quality Evaluation Factors. The quality evaluation set is a set of various total evaluation results that the evaluator may make to the evaluation object, which is represented by V: $V = \{v_1, v_2, \ldots, v_j, \ldots, v_m\}$, where v_j represents the j-th evaluation. As a result, m is the total number of evaluation results. In the process of establishing the evaluation set, establishing the membership degree of the evaluated index relative to each element of the evaluation set v_j is the key to correctly establishing the fuzzy set and making objective evaluation results. Through quantitative analysis, the dynamic development trend of reference-related series and comparison series can be found, using relative geometric relationships to process and compare the statistics for each series, and determine primary and secondary factors based on the magnitude of the correlation.

Therefore, the establishment of the membership function is extremely important in the fuzzy evaluation. For the evaluation of the comprehensive intelligence of music majors, use qualitative language to describe, and the evaluation set can be set as $V = \{$excellent, good, average, pass, poor$\} - \{v_1, v_2, v_3, v_4, v_5\}$. Then, the fuzzy judgment vectors F corresponding to the comment grades are: (Excellent (90–100), Good (80–89), Fair (70–79), Pass (60–69), and Poor (below 59)). The Sig. (two-sided) values of the paired sample test of the three groups of variables are all less than 0.01, showing differences at the 0.01 significance level. Based on the above test results, it can be concluded that before the teaching experiment began, the two classes were at the same level in listening, vocal comprehension, and total score. After a semester of teaching experiments, there was no statistically significant change in the average scores of students in the control class in all aspects, while the experimental class improved significantly in the three research areas of listening, vocal comprehension, and total score.

The system collects students' vocal music teaching data, and Figure 5 cleans, integrates, and transforms the data. To verify the application of the expert scale in practice, a trial evaluation was carried out on student A. 10 members of the expert evaluation team were invited to conduct an on-site evaluation of the multiple intelligences of student A's music major, and to evaluate them.

We select data sources according to different mining tasks, standardize the data using the standard parameters established before, perform the data transformation according to the needs of decision tree mining, and finally form effective data that can be mined. This paper adopts the basic evaluation model of the "Taylor Model," decomposes the target layer by layer, forms an indicator system and establishes a complete evaluation indicator system so that the evaluator can systematically and deeply study the evaluation object and grasp various relevant factors.

4. Application and Results Analysis

4.1. Multi-Intelligence Data Preprocessing. The post-test listening, vocal comprehension, and post-test music total scores of the students in the two classes were tested by the Levene of variance equation, and the Sig. values were all greater than 0.05, which met the requirement of equal variance. The Sig. (two-sided) values in the first row of each of the three data items are all less than 0.05, so the data in the three aspects are significantly different at this time. After the teaching experiment for one semester, the mean of the

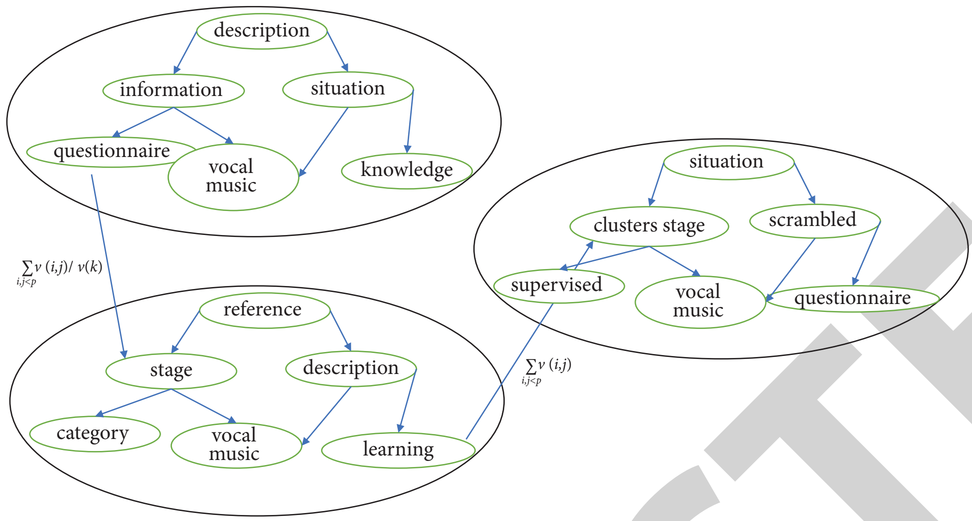

Figure 4: Vocal music teaching system architecture.

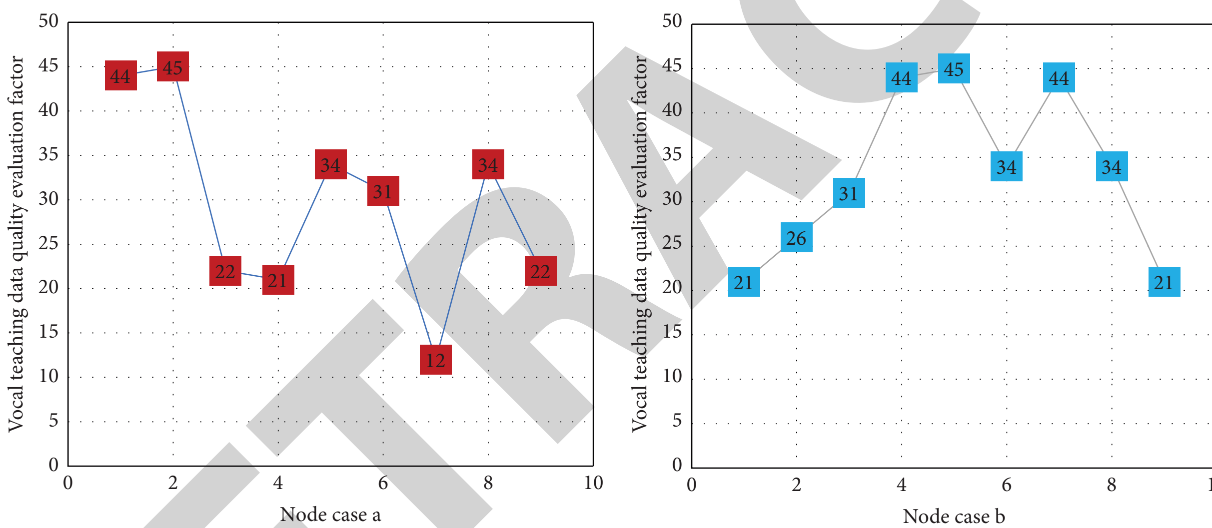

Figure 5: Quality evaluation factors of vocal music teaching data.

experimental class was higher than the control class in terms of listening scores, vocal comprehension scores, and total music scores. According to the mean variance t test results, the t values are all negative, and the Sig. (two-sided) values are less than 0.05.

It can be concluded that the music listening scores, vocal comprehension scores, and total music scores of the two classes are statistically significant. The significant difference in meaning, especially the Sig. (two-sided) value of the independent sample test of the mean equation t test of the listening score and the total score of music is less than 0.01, indicating that there is a very significant difference. The teaching experiment achieved good results in students' listening, vocal comprehension, and total scores, among which listening scores and total scores made the greatest progress.

The decision tree classifier created by the decision tree C4.5 model based on the information gain rate can be used in the classification and discrimination of the comprehensive evaluation of the quality index and has a high classification accuracy. The accuracy is not high in the evaluation and classification of vocal music teaching quality; Figure 6 uses multiple intelligence units to predict the classification of vocal music teaching quality and compares the effects of different penalty factors c and kernel parameters g, different kernel functions, and normalization implementation methods on vocal music teaching. All training patterns have a fixed root, and these patterns are recursively selected by the impurity function on the basis of being divided, and the division will continue until the end of all training patterns.

The influence of the quality classification accuracy: the bestc = 512, bestg = 1.3195 and [0 1] normalization based on the RBF kernel function are finally selected; because the multi-intelligent unit classification prediction is particularly dependent on the value of the penalty factor c and the kernel parameter g, this paper proposes a global optimization of

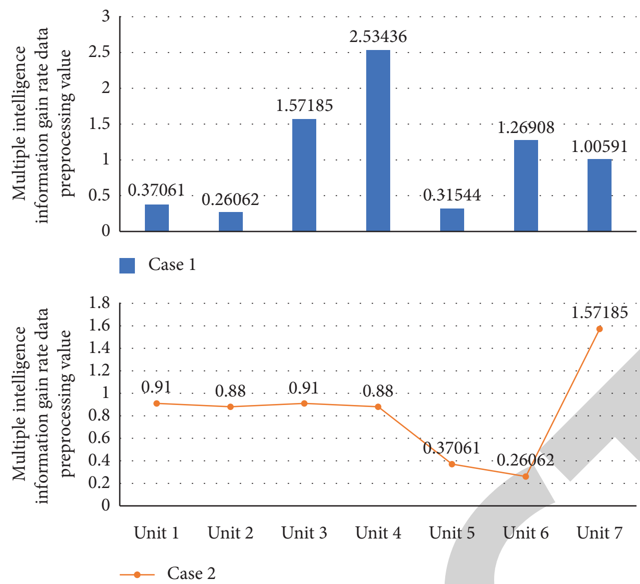

Figure 6: Data preprocessing of information gain rate of multiple intelligences.

parameters based on multiple intelligences, and compares the prediction accuracy and finds that the higher accuracy can be achieved. To reasonably reflect the comprehensive impact of all indicators, each index must be considered layer by layer. The comprehensive evaluation of each layer vectors can be represented as texts.

4.2. Simulation of Vocal Music Teaching Quality Evaluation. In this paper, six music indicators are used as the quality evaluation input layer, and there are five types of vocal music teaching quality levels. The number of input neurons of the neural network changes with the dimension of the input feature vector. The number of neurons in the hidden layer is 5, and the number of iterations is 1000, the network has stabilized, the learning rate is initially set to 0.1, and the expected error is set to 0.1. The role of the kernel function in the support vector machine is mainly to deal with nonlinear features in the high-dimensional feature space. The generalization ability of the multi-intelligence unit depends on the appropriate position of the parameters, such as the regularization factor c and the value of the kernel parameter g.

The unit position of the multiple intelligence unit is affected by the best position of the unit itself, and the influence of the best unit position in its neighborhood, when the field of a unit is the whole group, the best position in the vicinity is called the global optimal unit, the multi-intelligence unit is easy to implement and has no complicated parameter adjustment, and the convergence speed is fast, and global fast optimization search is possible.

In the flow of Figure 7, the function stopping_cond() is used to check whether all data belong to the same class or have the same attribute value, and decide whether to stop the growth of the decision tree by judging. The best_split() function determines the test condition attributes that split the training data. The function createdNode() establishes a new node for the decision tree, this node may be a test condition, denoted as node-test cond, and may also be a class label, denoted as a node. An entropy-based measurement is also employed, which can process nominal and categorical data and allow for large data collection in a short period of time.

For each survey question, if the student's score is 4 or 5, it can be considered that the student's inner feelings for the survey question are obviously positive. All training patterns have a fixed root, and these patterns are recursively selected by the impurity function on the basis of being divided, and the division will continue until the end of all training patterns. Returning to the question feedback of the questionnaire for the 50 students in the experimental class, after a semester of experimentation, the number of students who have an obvious positive feeling for the design content of these 20 survey questions has increased, and the specific changes are different. Figure 8 clearly shows the change in the ratio of self-assignment of 20 items to 4 or 5 in the two questionnaires before the experiment and after the experiment.

In the first principal component, the coefficients of each index variable are close, the values are not much different, and the load is close. This shows that the first principal component is jointly determined by seven indicators of language, mathematical logic, visual space, sound rhythm, body movement, interpersonal communication, self-introspection, and natural observation intelligence. It can be seen from the figure that the contribution rate of the principal component to the whole is the largest (33.125%), which shows that the ability of the principal component to comprehensive indicators is strong. The accuracy rate is 90.77%, and compared with the multi-intelligence unit, this paper adopts the multi-intelligence unit structure of 6-7-5 according to the data structure of the evaluation index. The number of output layers is 5, the number of input layers selected in this paper is 1 less than the number of hidden layers, the

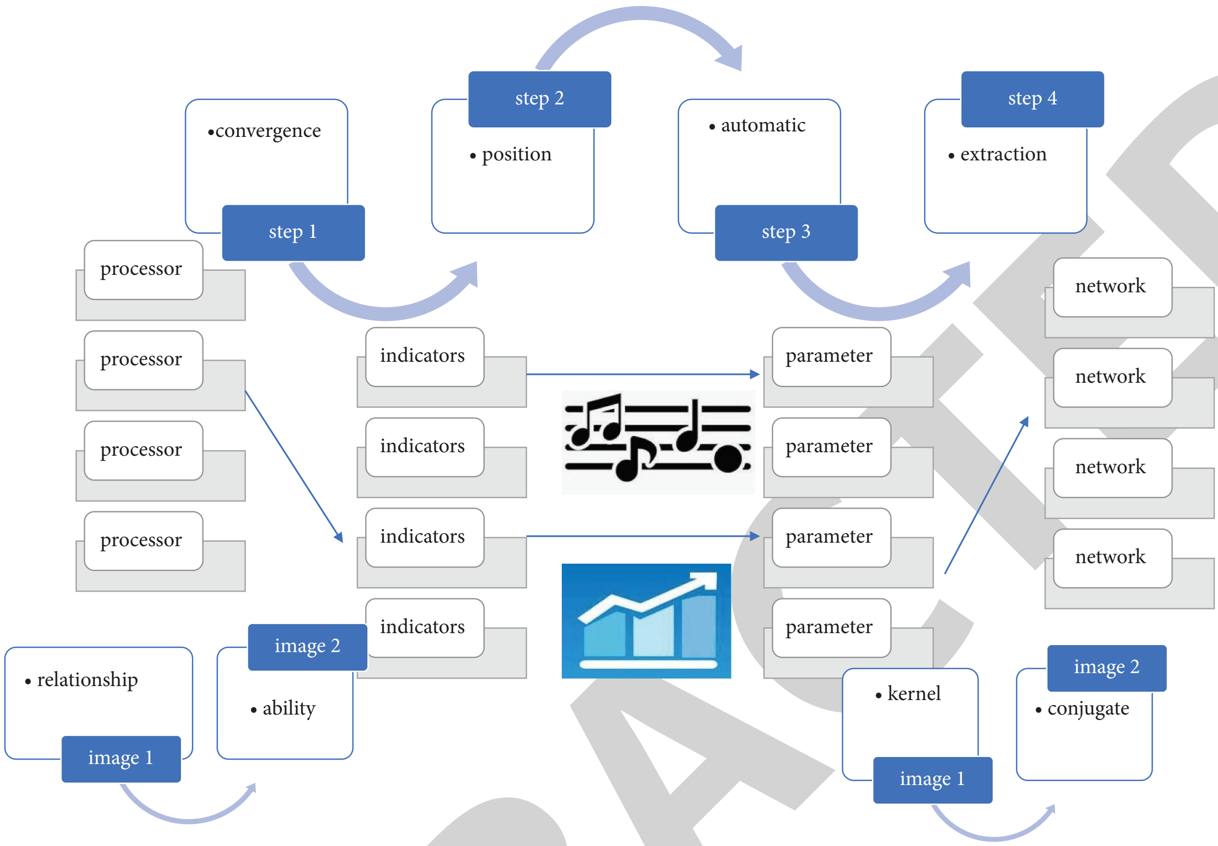

Figure 7: The evaluation process of vocal music teaching quality.

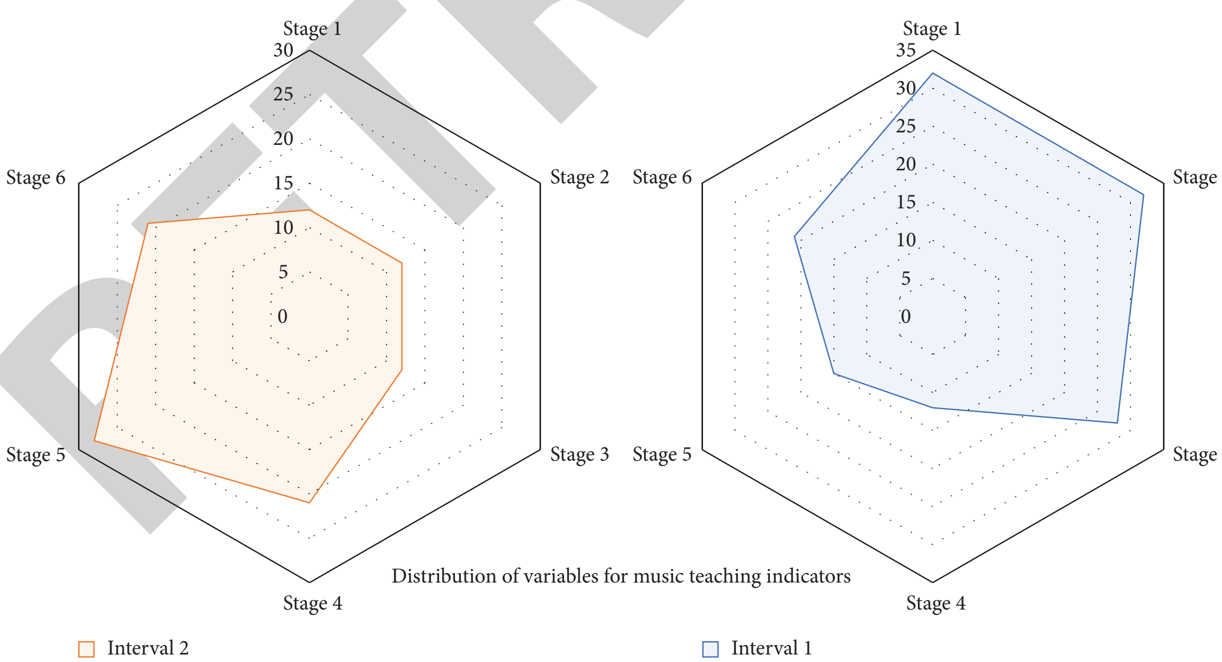

Figure 8: Coefficient distribution of music teaching index variables.

training function is trainlm, the number of learning steps is set to 1000, the learning rate is 0.1, and the transfer functions of the output layer and the hidden layer are tansig and purelin, the learning target is 0.0001, and the program is run multiple times, whichever has a higher accuracy rate. A certain accurate prediction is 51 (51/65), and the accuracy rate is 0.78, indicating that the multiple intelligence unit has a certain role in the classification of vocal music teaching quality.

5. Conclusion

Based on the theory of multiple intelligences, this paper establishes a quality evaluation model according to the characteristics of music majors' teaching evaluation work and realizes the development of a diversified student teaching evaluation system. The model analyzes the factors of students' teaching evaluation, abstracts them to form indicators, and establishes an indicator system of diversified evaluation subjects. In the determination of indicator weights, the cluster analysis method is used, and the fuzzy comprehensive evaluation model is used to obtain the evaluation results of students' evaluation. Finally, the students' comprehensive evaluation results are obtained. All evaluation data is designed as a database system and the data table is designed separately by type. It mainly includes five modules: system management, student teaching evaluation, student vocal music teaching evaluation, student evaluation result management, and evaluation model management. The experimental results show that the decision tree algorithm of data mining is used to classify the input students' vocal music teaching information, find the effective rules of the students' vocal music teaching information, check the students' vocal music teaching rules, and the key matching can facilitate the leaders to make vocal music teaching decisions.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

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