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Design and analysis of intelligent music visualization teaching system based on fuzzy median information

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SUMMARY: *In music teaching, in-depth mining of resource information and student characteristic information, etc. provides a new perspective of music resource application. This study introduces the fuzzy neutrosophic information theory into the design of intelligent music visualization teaching system, making full use of the correlation of information data. Solving the similarity of different types of resources, clustering and integrating music resources. Incorporate student personality characteristics/common characteristics/experience teaching strategy rules to generate intelligent instruction strategies. Weighted average resource feature importance and student interest, sort the overall interest, and improve the accuracy of resource recommendation. When the number of clusters is 5, the resource recommendation accuracy of the intelligent music visualization teaching system based on fuzzy neutrosophic information reaches 0.909-0.978, which is able to recommend appropriate music resources according to the actual situation of students.*

KEYWORDS: *music visualization teaching; fuzzy median information; resource clustering; strategy generation; interest degree*

1 Introduction

With its intuitive and figurative characteristics, music visualization teaching can promote students' understanding of knowledge and enhance their perception of abstract music [1]. The Art Curriculum Standards for Compulsory Education (2022 Edition) places special emphasis on practice orientation, requiring students to develop core literacy in diverse practices centered on artistic experiences. Only through actively participating in music activities, immersing themselves in the charm of music, and exploring different musical styles and cultural backgrounds can students truly appreciate the richness of music and draw endless inspiration and enlightenment from it. This process is the development and formation of students' thinking, as well as an important link for students to gain experience and improve their ability to transfer and apply knowledge [2-4]. To realize the change from emphasizing on learning music knowledge to emphasizing on music learning experience, visualization teaching strategy is undoubtedly one of the best choices.

Music visualization is a kind of audio-visual interaction, which presents the rhythm, melody, harmony, timbre and other elements of music through visual effects in order to let the listener understand and feel the music more intuitively. In music teaching, only when a variety of associative experiences such as listening, speaking, moving, dancing, acting, arranging and creating cooperate and resonate with each other, students' thinking and imagination can be truly

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stimulated [5-7]. Music visualization is also a visualization tool based on psychological theories, which stimulates the listener's affective and emotional responses through visual effects and enhances the expressive and infectious power of music [8-10]. In other words, visualization teaching can deepen students' artistic experience and develop their core literacy. In traditional music teaching, students have difficulties in absorbing abstract theoretical knowledge and lack of feedback mechanisms for practical skills [11, 12]. In recent years, intelligent teaching systems have flourished and become an important tool in the education system to achieve personalized instruction and feedback, and diversified forms to present abstract knowledge [13, 14]. Promoting the combination of intelligent teaching system and visual teaching mode can optimize the current music education mode and promote the improvement of students' academic performance.

Wang and Zhang [15] developed a visualization system for vocal music teaching through virtual reality technology to display vocal music knowledge in a more intuitive form, which is conducive to students' digestion of knowledge, and can also unite the traditional education methods to improve the effect of vocal music teaching. Li [16] used a deep neural network to construct a music emotion classification model and designed a music teaching visual system based on it to project audio emotions to virtual characters for emotional expression, which was used to visualize music emotions and promote students' understanding of music. Wu and Wu [17] incorporated an emotion recognition model in an interactive music visualization system to analyze and understand the association between music and emotion through a dataset optimized by a genetic algorithm and a support vector machine algorithm. Huang et al [18] created an artificial intelligence based music visualization system, consisting of three modules: music information retrieval, large-scale language model and image generation model, to visualize the input audio, for both normal and hearing impaired people by a better music perception experience. Zhang [19] established a music teaching analysis and intelligent assessment system with multimodal data fusion and deep learning technology, in which the visualization module presents students' learning performance visually, enabling teachers to obtain assessment feedback intuitively. Liang [20] developed a university vocal music teaching system based on bi-directional long and short-term memory networks and convolutional neural networks, covering functional modules such as voiceprint database, personalized feedback, real-time spectrogram visualization, real-time learning progress tracking, and artificial intelligence-based scoring mechanism. Li and Zhao [21] used a temporal difference reinforcement learning algorithm to automatically generate piano fingering, and designed a visualization strategy for piano learning by combining music-visual mapping rules as well as music visualization cases, and also featured an intelligent dialogue module to enhance students' interaction and sparring effects. An [22] integrates and audio feature extraction technology, visualization technology, machine learning and interactive mechanism to propose an intelligent music visualization teaching system, which improves students' mastery of theoretical knowledge, performance skills and creative ability with intuitive, efficient and personalized performance.

It can be seen that the music visualization teaching system is able to transform abstract music theoretical knowledge into visual content, and provide personalized feedback and evaluation to students, track students' learning progress, and possess a certain degree of interactivity. However, due to the existence of uncertainty factors in teaching, it limits the system's personalized teaching strategy generation and interactive effect. In addition, some music knowledge points and music characteristics have fuzzy characteristics, which make it difficult to accurately present visualization and personalized feedback. Fuzzy neutrosophic information is based on fuzzy logic to process uncertain and fuzzy information, which plays an important role in dealing with uncertain information in the system. Chen [23] used a fuzzy decision-making system to evaluate students' proficiency, music preference, and learning styles in music teaching, and generated personalized music teaching strategies based on the evaluation results in accordance with the characteristics of the students. Han [24] proposed a machine-learning-based fuzzy clustering pitch synthesis system for string sound, in which the fuzzy clustering model can analyze and simulate the acoustic properties of violin sound, so as to accurately estimate and classify pitch characteristics.

The application of fuzzy median information in the intelligent music visualization teaching system is reflected in three aspects. The first is to calculate the second-order similarity between clusters on the extracted adaptive feature measures of the center online music resources and offline music resources, and cluster and integrate different music resources. Secondly, based on the best clustered music resources, students' personality and common features, and fuzzy inference model, teaching strategy rules with weighted uncertainty representation with confidence are generated to provide rule guidance for resource recommendation. Third, we compare the similarity between resource features and students' interest level features to realize music teaching resource recommendation with high accuracy.

2 Intelligent music visualization teaching system design

2.1 Fuzzy sets and fuzzy logic

2.1.1 Fuzzy sets and affiliation functions

1) Basic Definition

A fuzzy set represents the degree to which an element belongs to a given set. The characteristic function of a fuzzy set is allowed to take values between 0.0 and 1.0 and represents the degree of affiliation of an element in a given set.

Definition 1: A fuzzy subset A on a given theoretical domain U is a mapping from the given theoretical domain U to the interval $[0.0,1.0]$:

$$\mu_A : U \to [0.0,1.0] \quad u \mapsto \mu_A(u) \in [0.0,1.0] \tag{1}$$

The mapping μ_A is called the affiliation function of the fuzzy subset A, and $\forall u \in U$ corresponds to a deterministic value $\mu_A(u) \in [0.0,1.0]$, which is called the degree of affiliation of $u \in U$ to A. If $\mu_A(x) = 0.0$, then x does not belong to A at all; if $\mu_A(x) = 1.0$, then x belongs to A at all; and if $0.0 < \mu_A(x) < 1.0$, then x belongs to A with the degree of affiliation $\mu_A(x)$.

2) Basic operations of fuzzy sets

Definition 2: Let A, B be two fuzzy sets on the same domain, whose affiliation functions are $\mu_A(x)$ and $\mu_B(x)$, the concatenation and intersection of A and B are denoted as $A \cup B$ and $A \cap B$ respectively, and the complementary set is denoted as $\bar{A}$. Their affiliation functions are:

$$\mu_{A \cup B}(x) = \mu_A(x) \vee \mu_B(x) = \max\{\mu_A(x), \mu_B(x)\} \quad \forall x \in U \tag{2}$$

$$\mu_{A \cap B}(x) = \mu_A(x) \wedge \mu_B(x) = \min\{\mu_A(x), \mu_B(x)\} \quad \forall x \in U \tag{3}$$

$$\mu_{\bar{A}}(x) = 1.0 - \mu_A(x) \quad \forall x \in U \tag{4}$$

2.1.2 Fuzzy logic

Fuzzy logic can deal with uncertain matters in a very intuitive and natural way. Arithmetic and Boolean operations are performed through fuzzy sets to describe the reasoning system of fuzzy rules.

1) Fuzzy propositional representation

A statement containing a fuzzy concept, fuzzy data or with a degree of certainty becomes a fuzzy proposition. It is generally expressed in the form of $X \ is \ A$ or $X \ is \ A(CF)$ where X is a variable on the threshold of the argument to represent the attributes of the object under discussion; A is a fuzzy concept or a fuzzy number, which is inscribed with the corresponding fuzzy set and subordinate function; and CF is the degree of certainty or the degree of likelihood of the occurrence of the corresponding event of the fuzzy proposition, which can be either a definite number or a fuzzy number or a fuzzy linguistic value. The so-called fuzzy linguistic value refers to the modifier that indicates the degree of size, length, speed, how much and so on. Specific applications can determine their own set of fuzzy linguistic values according to the actual needs.

2) Fuzzy Rule Representation

Each fuzzy rule has the general format of conditional proposition: fuzzy If-then rule, also called implication. The general form of a fuzzy rule is:

$$If \ E \ then \ H(CF, \lambda) \tag{5}$$

where E is a fuzzy condition expressed in terms of a fuzzy proposition, which can be either a simple condition expressed by a single fuzzy proposition or a combined condition consisting of multiple fuzzy propositions; H is a fuzzy conclusion expressed in terms of a fuzzy proposition; CF is the credibility factor of a fuzzy rule, which can be either a definite number or a fuzzy number or a fuzzy linguistic value; and λ is the threshold of the rule, which is used to indicate the limitations within which the rule can be used.

2.2 Fuzzy clustering based music teaching resources integration

The degree of aggregation of music resources depends mainly on the similarity between the central online and offline music resources. However, for the complementary relationship of music resource integration, it is precisely necessary to aggregate and store sub-databases of different music resource categories. For this reason, it is necessary to use inverse clustering scoring methods for individual metrics to effectively integrate online and offline music resources.

Read the teaching music resource information to be processed and extract the adaptive feature quantity W of the music resource information. Considering the attribute characteristics of integrating teaching music resources, the scale size when integrating music resources is constrained, and the specific calculation formula is:

$$q = \frac{r \cdot \log a}{A \cdot W} \tag{6}$$

where: A is the total amount of data transferred; r is the feature vector; $\log a$ is the data variance.

According to the goal of music resource integration and the data format within the system database, teaching music resources are globally extracted and the inter-cluster similarity R_{ij} of the data in the clustering center is calculated. The online teaching music resources are formulated as sample x and offline teaching music resources as sample y, then the dissimilarity D_{xy} between the two samples in terms of numerical type attributes can be described as:

$$D_{xy} = \sum_{A'} (x_k - y_k)/q \tag{7}$$

where: A' is a numerical attribute of the music resource; k is the number of complete samples.

The second order similarity between clusters of the data at the clustering center is:

$$R'_{ij} = \sum_{i=1}^{k} \frac{e \cdot R'_{ijk}}{D_{xy}} \tag{8}$$

where: e is the missing value of relevant information supplement; R'_{ijk} is the median filler value of the data.

According to the calculated second-order correlation, the structure matrix of teaching music resource integration is constructed, and the music resource integration function is obtained as:

$$\min \sum b_i = L^* + \beta \tag{9}$$

where: b_i is the system communication capacity; L^* is the set of physical nodes for music resources integration; β is the number of clustering centers.

When integrating the information of teaching music resources, the information affiliation degree and the single clustering center of a single cluster are obtained by calculating the extreme value of Eq. (9), and then a new clustering center is selected, and the process of solving the extreme value of Eq. (9) is repeated until a new clustering center is no longer generated, and the fuzzy clustering process is stopped. The final output of the fuzzy clustering result is the final result of the integration of online and offline teaching music resources.

2.3 Modeling of teaching strategies based on fuzzy reasoning

2.3.1 Basic Models of Fuzzy Reasoning

There are three basic modes of reasoning in fuzzy reasoning, namely: fuzzy hypothetical reasoning, fuzzy rejective reasoning, and fuzzy trinitarian reasoning.

1) Fuzzy hypothetical reasoning

Let A and B be fuzzy sets on the domains U and V, respectively, with the following rules:

$$\text{If } x \text{ is } A \text{ then } y \text{ is } B \tag{10}$$

If there is a fuzzy set A' on U that can be fuzzy matched with A, then it follows that y is B' and B' is a fuzzy set on V. Call this fuzzy reasoning as fuzzy hypothetical reasoning.

2) Fuzzy Rejective Reasoning

Let A and B be fuzzy sets on the domains U and V, respectively, with the following rules:

$$\text{If } x \text{ is } A \text{ then } y \text{ is } B \tag{11}$$

If there is a fuzzy set B' on V that can be fuzzy matched with B, then it follows that x is A' and A' is a fuzzy set on U. Call this fuzzy reasoning as fuzzy rejective reasoning.

3) Fuzzy Trinitarian Reasoning

Let A, B, and C be fuzzy sets on the domains U, V, and W, respectively, and if by the chain of rules

$$\begin{array}{l} \text{If } x \text{ is } A \text{ then } y \text{ is } B \\ \text{If } y \text{ is } B \text{ then } z \text{ is } C \end{array} \tag{12}$$

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$$\text{If } x \text{ is } A \text{ then } z \text{ is } C \tag{13}$$

Then the fuzzy reasoning is called fuzzy trinitarian reasoning, or fuzzy sequential reasoning law.

2.3.2 Smart Music Visualization Teaching Strategy Model

For accurate representation and reasoning of the strategy rules, the strategy rules are represented using a weighted uncertainty representation with plausibility in the following form:

$$\text{R: If } E_i(\omega_i) \text{ Then } H(\text{CF}(H,E),\lambda) \tag{14}$$

where E_i is the precondition of the rule, which can be either a simple condition or a combination of multiple simple conditions connected by AND; H is the conclusion, which can be a single conclusion or a combination of conclusions connected by AND. $CF\left(H,E\right)$ is the credibility of the rule, known as the credibility factor (CF) or strength of the rule, which is a quantitative representation of the degree of belief that something is true, and whose initial value is determined by the domain expert. λ is the threshold value that sets a limit on the applicability of the corresponding rule, which is only possible if the credibility $CF(E_i)$ of the precondition E_i meets or exceeds this limit, i.e., $CF(E_i) \geq \lambda$. The $\omega_i\left(i=1,2,\ldots,n\right)$ is a weighting factor, the values of which are all given by domain experts.

$$\sum_{i=1}^{n}\omega_i = 1.0\left\{0.0 \leq \omega_i \leq 1.0, (i=1,2,\ldots,n)\right\} \tag{15}$$

$$R = \begin{cases} \text{Apply Rules} & CF(E_i) \geq \lambda \\ \text{Do Not Apply Rules} & CF(E_i) < \lambda \end{cases} \tag{16}$$

1) Learner personality profile rule model:

Rule information: =<rule identifier, learner identifier, condition identifier set, conclusion identifier set, rule category, keyword, confidence level, λ threshold, extended information>

Conditional information: =<conditional identifier, keywords, content, weighting factors, extended information>

Conclusion information: =<conclusion identifier, keywords, content, extended information>

2) Learner Common Characteristics Rule Model:

Rule information: =<rule identifier, learner identifier set, condition identifier set, conclusion identifier set, rule category, keyword, confidence, λ threshold, extended information>

Conditional information: =<conditional identifier, keyword, content, weighting factor, extension information>

Conclusion information: =<conclusion identifier, keywords, content, extended information>

3) Empirical teaching strategy rule model:

Rule information: =<rule identifier, expert identifier, condition identifier set, conclusion identifier set, rule category, keyword, confidence level, λ threshold, extended information>

Conditional information: =<conditional identifier, keywords, content, weighting factors, extended information>

Conclusion information: =<conclusion identifier, keywords, content, extended information>

Teaching strategies are derived from the library of teaching strategies in the Intelligent Music Visualization Teaching System and can be either learner characteristic rules or empirical teaching strategy rules. Learner characteristic rules take Web logs and learner model information over a period of time as source data, and are analyzed by the learner characterization module to generate primitive personality and common characteristic rules with the participation of teaching experts. After a series of processing, such as rule transformation, conflict resolution, synthesis, and updating, the original strategy rules form standardized individuality and commonality feature rules to be deposited into the teaching strategy library, which can be used as teaching strategies to intelligently guide the learners' learning together with the empirical teaching strategies given by the experts to provide the learners with the best resource recommendation paths.

2.3.3 Personalized Recommendation of Resources under Fuzzy Logic Matching Resource Requirements

Since the extracted features also have some features that are not directly related to students' needs, these features not only increase the computational complexity, but also interfere with the accuracy of the recommendation model. Through feature relevance assessment, these irrelevant and redundant features can be eliminated, thus improving the efficiency and accuracy of recommendation. Feature relevance refers to the relationship between multiple features in a dataset. By comparing each feature in the intelligent music curriculum resources with the fuzzy model of students' interests, the correlation between them is assessed. The benefit of this approach is to understand students' interest preferences more accurately, thus improving the accuracy of recommendation, for which the feature interest degree f is calculated by feature relevance assessment.

$$f = \sum_{j=1}^{m} w_{ij} \cdot s_{ij} \tag{17}$$

where w_{ij} is the weight of the j th sub-attribute of the i th feature; s_{ij} is the similarity between the sub-attribute and the student preference profile; and m is the number of sub-attributes of the feature.

The overall interest degree P of the resource is calculated by aggregating the interest degrees f of all features, using a weighted average, and assigning different weights according to their importance and the degree of influence on students' interests, as shown in Equation (18):

$$P = \sum_{i=1}^{N} \xi_i \cdot f_i \tag{18}$$

where ξ_i is the weight of the i th feature, which satisfies $\sum_{i=1}^{n} \xi_i = 1.0$; and N is the number of features of the intelligent music curriculum resources.

Considering the influence of feature interest degree f_i on the weights ξ_i of intelligent music curriculum resources, this paper introduces the adjustment factor $g(f_i)$, and adjusts the weights by Equation (19):

$$\xi_i' = g(f_i)\xi_i \tag{19}$$

where $g(f_i)$ is an increasing function, meaning that the higher the feature interest degree, the higher the weight of that feature.

From this, the overall interest degree is updated and calculated as:

$$P' = \sum_{i=1}^{N} \xi_i' \cdot f_i \cdot X^2(i) \tag{20}$$

According to the height of P' , the sorted resource list R_t is obtained.

This process makes full use of the fuzzy model of student interest and adaptive feature quantity to realize the personalized recommendation of intelligent music course resources based on fuzzy logic, which can not only improve the accuracy of recommendation, but also significantly enhance the personalization of student experience.

2.4 Intelligent music visualization teaching mode construction

Based on cognitive psychology, constructivism and fuzzy neutrosophic information theory, this study introduces a fuzzy neutrosophic information-based intelligent music visualization teaching system in music teaching to achieve targeted and effective recommendation of music resources, and to provide assistance to students' learning and teachers' teaching. The model is based on the following principles: “student-oriented, visual stimulation; scientific guidance, scaffolding; learning-centered, hierarchical growth; sequential learning, each beautiful; creative expression, interactive experience; grasping the elements of self-confidence, task-driven, effective strategies; independent inquiry, creative practice; integration of the whole, immersed in learning; based on the unit, disciplinary nurturing; refining the quality of the classroom shaping people; set up a grand ambition, brighten the self”. The visual teaching strategy of “integrating students' learning information, fuzzy clustering of music resources, modeling of teaching strategies, weighted calculation of interest degree, and matching and recommending of resources” is used to accurately design and scientifically push forward the implementation of teaching objectives and tasks in the teaching process. -In the process of assimilating, balancing and adapting to the visualization of music teaching practice, we can maximize the benefits of visualization teaching, and build a solid classroom position to realize subject education.

3 Intelligent music visualization teaching system application effect test

3.1 Analysis of the effect of music teaching resources integration based on fuzzy clustering

3.1.1 Study of the relationship between the number of clusters and the mean error

The designed intelligent music visualization teaching system based on fuzzy neutrosophic information is applied to the music teaching resources integration, teaching strategy generation and teaching resources recommendation in college D to test the performance level of the system. Table 1 shows the relationship between the number of resource clusters and the average error of the final teaching resource recommendation effect obtained from several experiments. When the number of resource clusters is gradually increased from 1 to 10, the average error tends to decrease and then increase. When the resource clustering is 5 classes, the average error of multiple trials reaches the minimum of 0.618.

Table 1: AE between number of resource clusters and recommendation effect

Number of resource clusters	Average error		
	Maximum value	Minimum value	Average value
1	0.952	0.927	0.940
2	0.944	0.913	0.929
3	0.850	0.796	0.823
4	0.815	0.764	0.790
5	**0.622**	**0.613**	**0.618**
6	0.759	0.720	0.740
7	0.793	0.845	0.819
8	0.836	0.902	0.869
9	0.877	0.941	0.909
10	0.905	0.968	0.937

3.1.2 Calculation of average cumulative gain from resource integration

Compare the average cumulative gain of resource integration of the model when the resource clustering is 1, 3, 5, 7 and 9, and judge the effect of resource integration under different number of clusters in Figure 1. When the resource clustering is 5, the average cumulative gain of resource integration of the model is the largest and the most stable, reaching 2.624~2.975. Therefore, in order to improve the accuracy of resource integration, the number of resource clustering is set to 5.

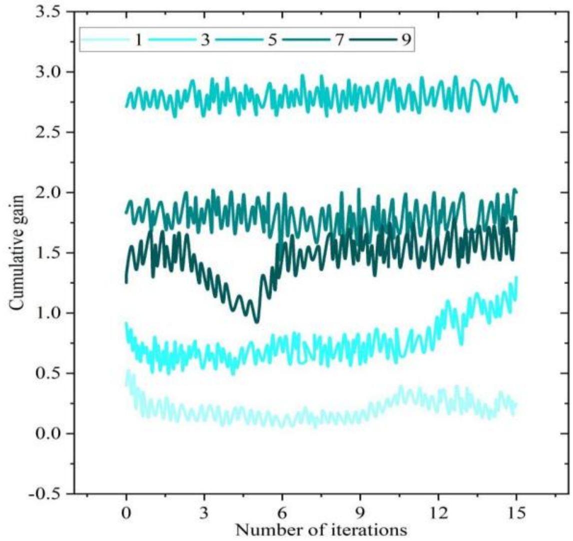
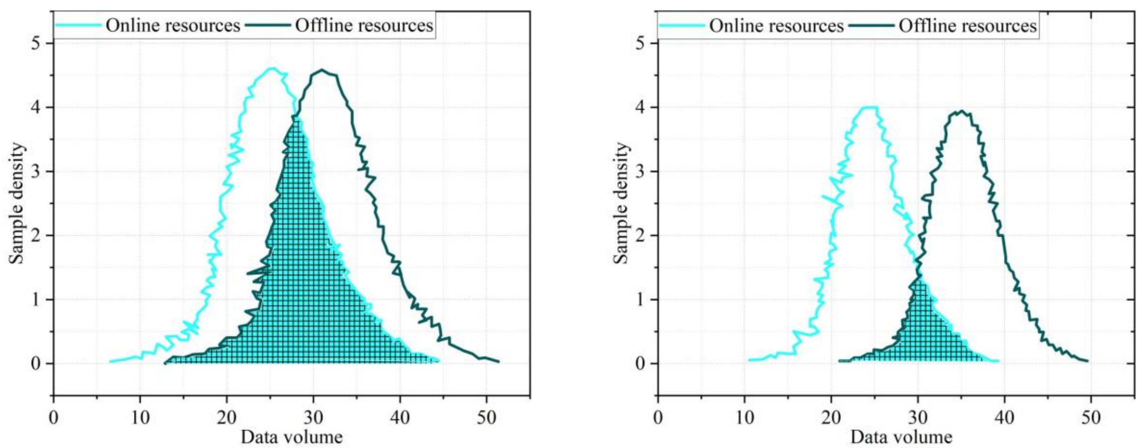


Figure 1: Effect of resource integration under the same clustering number

3.1.3 Comparison of clustering area of different methods

Compare the clustering and integration effects of the fuzzy clustering-based music teaching resource integration method and the cross-modal integration method. The 2 methods are used to integrate online music resources and offline music resources data, and the area of clustering of online music resources and offline music resources data is obtained by intersecting the expectation curves generated during the calculation process. The larger the area is, the better the clustering effect is. Figure 2 shows the clustering area results of the 2 methods. The clustering area of the fuzzy clustering-based music teaching resource integration method is significantly smaller than that of the cross-modal integration method, with the horizontal coordinate only spanning 20.0-40.0 and the vertical coordinate only in the range of 0.0-1.5. In contrast, the horizontal coordinates of the clustering area of the cross-modal integration method span 12.5-45.0, and the vertical coordinates are as high as 4.0.The fuzzy clustering-based music teaching resource integration method has better clustering effect of music teaching resources, and improves the effect of recommending intelligent music visual teaching resources based on fuzzy median information.



(a) Cross-modal integration method

(b) Music teaching resource integration method based on fuzzy clustering

Figure 2: The clustering areas of the two methods

3.1.4 Comparison of data redundancy of different methods

Figure 3 compares the data redundancy of the 2 methods for clustering data from 60 resource samples. clustering of 60 music resource samples, the data redundancy of the fuzzy clustering-based music teaching resource integration method is only 0.007~0.141, and the data redundancy of the cross-modal integration method reaches a higher level of 0.513~0.686. From the results of data redundancy comparison of clustering, the fuzzy clustering based music teaching resources integration method also achieved better results in this index.

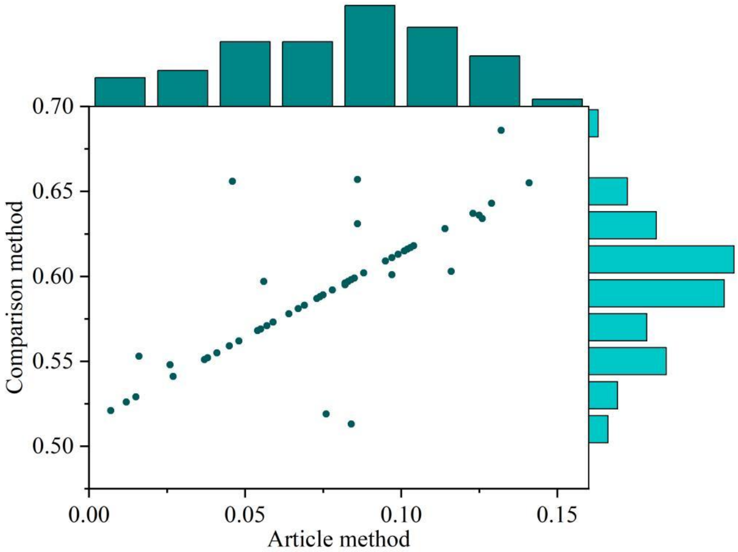


Figure 3: The redundancy of clustering data for the two methods

3.2 Examining the Effectiveness of Instructional Strategy Generation Based on Fuzzy Reasoning

3.2.1 Teaching Strategies to Blur Credibility

Based on the fuzzy clustering results of music resources, corresponding teaching strategies are generated. As an example, 20 sample data of the above five categories were combined with each clustered music resource feature to generate 10 teaching strategies. Figure 4 shows the fuzzy credibility of each sample data in the 10 teaching strategies.The fuzzy credibility of the 20 sample data in the 10 teaching strategies ranges from 0.5 to 1.0, and most of them are concentrated in the range of 0.6-0.8, which indicates that the credibility of the generated teaching strategies is higher, which also indicates that the effect of resource clustering is better.

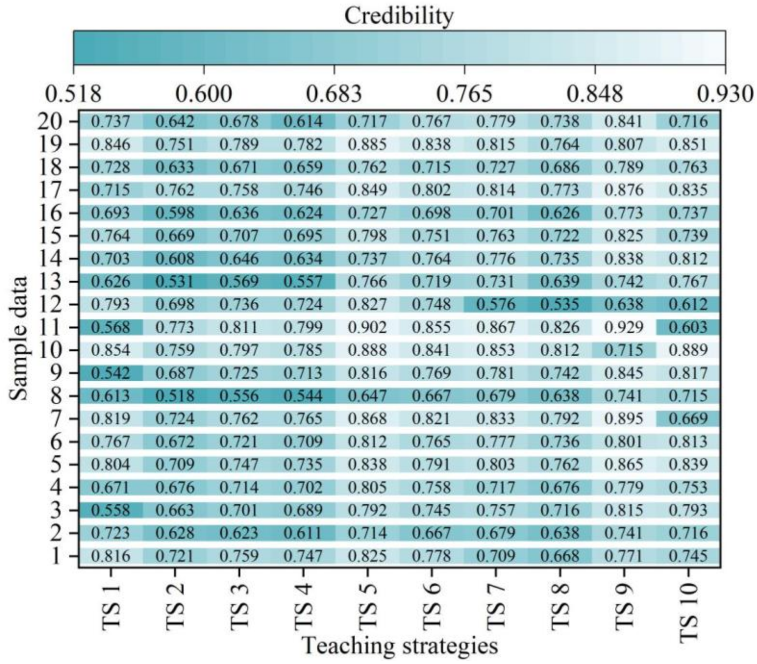


Figure 4: Credibility of sample data among 10 teaching strategies

3.2.2 Clustering Affiliation of Instructional Strategies

Figure 5 shows the results of the affiliation degree calculation for the 10 teaching strategies under the 5 teaching resources clusters. From the results of affiliation calculation, the affiliation of all 10 teaching strategies is high, reaching the range of 0.600-0.900, with the highest being 0.858 for strategy 5 in cluster 3. The higher affiliation indicates that the system-generated teaching strategies can better utilize the integrated 5 categories of music teaching resources, which also helps to improve the accuracy of the recommendation of teaching resources.

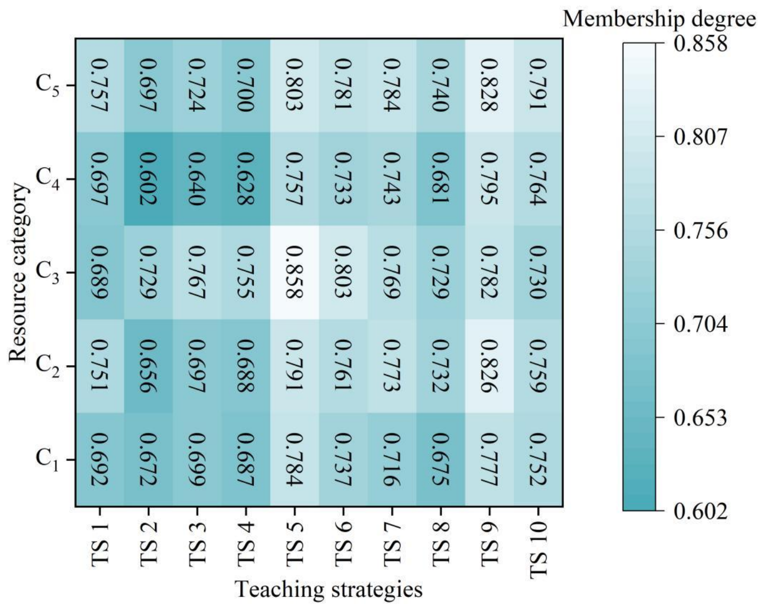


Figure 5: Degree of membership of 10 teaching strategies under 5 clusters

3.3 Analysis of resource recommendation effect under fuzzy logic matching

3.3.1 Recommendation accuracy of teaching resources for different students

The recommendation of music teaching resources is completed by combining the learning situation of 30 students majoring in cello in the School of Music of University D with the weighting of feature interests and other calculations. Table 2 counts the accuracy of the resources recommended by the intelligent music visualization teaching system for 30 students. The precision of the resources recommended by the system according to the 30 students' situations all reached more than 0.900, with a minimum of 0.909 and a maximum of 0.978, which is a high recommendation precision.

Table 2: Accuracy of the system's recommendation of 30 student resources

Student ID	Accuracy	Student ID	Accuracy
1	0.964	16	0.931
2	0.925	17	0.952
3	0.917	18	0.963
4	0.950	19	0.967
5	0.936	20	0.931
6	0.962	21	0.971
7	0.938	22	0.965
8	0.922	23	**0.909**
9	0.946	24	0.973
10	0.951	25	**0.978**
11	0.967	26	0.914
12	0.932	27	0.959
13	0.958	28	0.955
14	0.919	29	0.946
15	0.946	30	0.943

3.3.2 Comparison of resource recommendation accuracy of different methods

Intelligent music visualization teaching system based on PageRank algorithm and intelligent music visualization teaching system based on IPCM with fusion recommendation algorithm are chosen as comparisons, and suitable music resources are also recommended for these 30 students. Table 3 shows the comparison results of music resource recommendation accuracy of the three methods. The recommendation accuracy range of the intelligent music visualization teaching system based on PageRank algorithm is [0.431,0.679], and that of the intelligent music visualization teaching system based on IPCM and fusion recommendation algorithm is [0.546,0.786], which are lower than that of the intelligent music visualization teaching system based on fuzzy neutrosophic information of [0.909,0.978]. Using the intelligent music visualization teaching system based on fuzzy median information, it can provide students with music teaching resources that are more in line with their needs, interests, and accuracy, clarify their music learning paths, and improve their music skills.

Table 3: Comparison of accuracy of resource recommendations for 3 methods

Student ID	Method		
	Ours	PageRank	IPCM and Integration
1	0.964	0.607	0.738
2	0.925	**0.431**	0.704
3	0.917	0.623	0.732
4	0.950	0.556	0.765
5	0.936	0.642	0.771
6	0.962	0.668	0.707
7	0.938	0.644	0.753
8	0.922	0.628	0.737
9	0.946	0.652	0.761
10	0.951	0.557	0.736
11	0.967	0.673	0.682
12	0.932	0.638	0.747
13	0.958	0.464	0.773
14	0.919	0.625	0.754
15	0.946	0.652	0.761
16	0.931	0.537	0.746
17	0.952	0.658	0.574
18	0.963	0.669	0.778
19	0.967	0.673	0.782
20	0.931	0.637	**0.546**
21	0.971	0.477	**0.786**
22	0.965	0.671	0.678
23	**0.909**	0.615	0.724
24	0.973	**0.679**	0.588
25	**0.978**	0.484	0.703
26	0.914	0.602	0.729
27	0.959	0.665	0.774
28	0.955	0.661	0.727
29	0.946	0.452	0.761
30	0.943	0.649	0.758

4 Conclusion

In this study, the introduction of fuzzy median information is used to improve the resource recommendation accuracy of the intelligent music visualization teaching system to assist students' music learning.

In the resource integration session, when the number of clusters is 5, the average recommendation error of music resources is 0.618, which is smaller than the number of other clusters. Moreover, the average cumulative gain of resource integration reaches 2.624-2.975, with the smallest clustering area and only 0.007-0.141 data redundancy.In the teaching strategy generation session, the credibility of the 10 teaching strategy rules generated is 0.5-1.0, and the final affiliation is in the range of 0.600-0.900. In the resource recommendation session, the resource recommendation accuracy of 30 students reached 0.909-0.978, which was significantly better than the other 2 systems.

The application of fuzzy neutrosophic information to the intelligent music visualization teaching system reaches the goals of optimizing the effect of resource integration, improving the personalized level of resource recommendation, and enhancing the wisdom ability of music teaching.

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References

[1] Park, E. J. (2025). Music dynamics visualization for music practice and education. Multimedia Tools and Applications, 1-17.

[2] Vass, E., & Deszpot, G. (2017). Introducing experience-centred approaches in music teacher education—Opportunities for pedagogic metamorphosis. Thinking Skills and Creativity, 23, 1-16.

[3] Costes-Onishi, P., & Kwek, D. (2023). Inquiry-based learning in music: Indicators and relationships between key pedagogical practices and the quality of critical thinking. Research Studies in Music Education, 45(2), 362-378.

[4] Ülger, K. (2018). The role of art education on the creative thinking skills of students in music and visual arts education: a comparison from the perspective of the music education. Abant İzzet Baysal Üniversitesi Eğitim Fakültesi Dergisi, 18(2), 1175-1195.

[5] Fortuna, S. (2017). Embodiment, sound and visualization: A multimodal perspective in music education. Zbornik radova Akademije umetnosti, 5(5), 120-131.

[6] SELMANI, T. H. (2023). MUSIC VISUALIZATION METHOD FOR AGES 5-7 YEARS OLD. PHILOSOPHICA International Journal of Social and Human Sciences, 10(19-20), 186-196.

[7] Zhang, X. (2023). Multi-sensory research of singing visualization in pre-school music education. Interactive Learning Environments, 31(5), 2830-2840.

[8] Dharmapriya, J., Dayarathne, L., Diasena, T., Arunathilake, S., Kodikara, N. D., & Wijesekera, P. (2023). Emotion Based Music Visualization with Fractal Arts. In IMPROVE (pp. 111-120).

[9] Yi, X. (2025). Analysis of students’ emotion based on visual clues in online music

teaching. Journal of Computational Methods in Sciences and Engineering, 14727978251341493.

[10] Sularso, S., Wadiyo, W., Cahyono, A., Suharto, S., & Pranolo, A. (2025). A Comprehensive Visualization for Music Education and Artificial Intelligence. JOIV: International Journal on Informatics Visualization, 9(2), 718-727.

[11] Obeng, P., & Osei-Senyah, E. (2018). The challenges of music teaching and learning in primary schools in Offinso South Municipality. Journal of Education and practice, 9(27), 45-49.

[12] Huang, H., Soontorntanaphol, N., & Wangphanich, C. (2025). Research and Development of Teaching Models for Music Theory Courses in Music Performance Majors. Pakistan Journal of Life & Social Sciences, 23(1).

[13] Lin, F., & Chen, F. (2025). Intelligent music education system: utilizing algorithms for personalized learning experience. International Journal of High Speed Electronics and Systems, 2540253.

[14] Lu, L. (2025). AI-powered intelligent music education systems for real-time feedback and performance assessment. International Journal of Information and Communication Technology, 26(18), 33-47.

[15] Wang, A., & Zhang, L. (2022). Design and implementation of computer visualization assisted vocal music teaching system. Computer-Aided Design and Applications, 19, 44-55.

[16] Li, Y. (2022). Music aesthetic teaching and emotional visualization under emotional teaching theory and deep learning. Frontiers in Psychology, 13, 911885.

[17] Wu, F., & Wu, H. (2023, June). Application of Emotion Recognition Technology Based on Support Vector Machine Algorithm in Interactive Music Visualization System. In International Conference on Computational Finance and Business Analytics (pp. 515-524). Cham: Springer Nature Switzerland.

[18] Huang, J., Weber, C. J., & Rothe, S. (2025, June). An AI-driven Music Visualization System for Generating Meaningful Audio-Responsive Visuals in Real-Time. In Proceedings of the 2025 ACM International Conference on Interactive Media Experiences (pp. 258-274).

[19] Zhang, L. (2024, August). Multimodal Music Teaching Analysis and Intelligent Evaluation System Based on Neural Network. In International Conference on Computational Vision and Robotics (pp. 551-561). Cham: Springer Nature Switzerland.

[20] Liang, L. (2025, August). Design and Development of University Vocal Music Teaching System Based on Optimized Neural Network. In 2025 Third International Conference on Networks, Multimedia and Information Technology (NMITCON) (pp. 1-7). IEEE.

[21] Li, S., & Zhao, R. (2024). Establishment and application of diversified piano teaching system in colleges and universities from the perspective of artificial intelligence. J Appl Sci Eng, 27(7), 2813-2823.

[22] An, R. (2024). Design and implementation of intelligent music visual teaching system. Journal of Computational Methods in Sciences and Engineering, 14727978251376187.

[23] Chen, Y. (2025). Innovation of music teaching methods in universities based on fuzzy decision support systems and deep learning. International Journal of Fuzzy Systems, 1-20.

[24] Han, Y. (2024). Fuzzy Cluster Pitch Synthesis System for the Violin Sound with Machine Learning. International Journal of Maritime Engineering, 1(1), 689-700.