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Article

A Study on Optimizing the Learning Effectiveness of Copyright Knowledge in Music Copyright Education Using the Random Forest Algorithm

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Abstract: With the continuous development of science and technology, the issue of learning copyright knowledge in music copyright education has become increasingly severe. In response to the problems highlighted above, this paper proposes a study on optimizing the effectiveness of copyright knowledge learning based on the random forest algorithm. By integrating music copyright education issues and three principles for constructing an evaluation system, this study establishes an evaluation indicator system for copyright knowledge learning effectiveness. Under the influence of the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation Method, the evaluation indicators are quantified. Based on this, the Random Forest algorithm is utilized to optimize the quantified data of each evaluation indicator, followed by an exploration of the optimization effects of the Random Forest algorithm. The optimization values of the four algorithms are 3.9365, 3.7213, 3.7323, and 3.7088, respectively. It can be concluded that the optimization effect of the RF (random forest) algorithm is higher than that of the DT (decision tree algorithm), LSTM (long short-term memory network), and LR (logistic regression), verifying the practical applicability and application value of the research scheme proposed in this paper, which has practical strategic significance for improving music copyright education.

Keywords: analytic hierarchy process; fuzzy comprehensive evaluation method; random forest algorithm; music copyright education

1. Introduction

Music copyright refers to the rights enjoyed by the original creators of musical works under copyright law, including the rights of reproduction, distribution, performance, adaptation, and so on [1-3]. It acts as a “protective umbrella” for musical works, safeguarding the legitimate rights and interests of creators and related parties in the music industry [4-5]. Music works encompass a wide range of forms, including songs, instrumental pieces, and more. Copyright is established from the moment a song is composed, starting with the lyrics and melody [6-8]. The composer holds copyright over the melody they create, while the lyricist holds copyright over the lyrics. If a music work is created through collaboration, all parties involved jointly hold copyright [9-10].

Copyright grants the rights holder various rights. First is the right of reproduction, meaning that others cannot reproduce the musical work without permission, such as privately burning CDs or photocopying sheet music [11-12]. There is also the right of distribution, allowing the rights holder to decide how and where the work is distributed, such as through a record company [13-14]. The right of performance is also crucial, as it specifies who has the right to publicly perform the musical work. For example, singers performing songs at concerts must obtain the necessary performance rights permission [15-16]. Additionally, there is the right of information network dissemination. With the widespread development of the internet, the dissemination of musical works online must be authorized by the rights holder. For instance, music platforms streaming songs must obtain the necessary copyright [17-19]. Music copyright not only provides economic returns to music creators and the music industry but also serves as an incentive mechanism to encourage creation [20-21]. The protection of music copyright also helps maintain the reputation and dignity of artists and promotes the prosperous development of music culture [22]. The purpose of music copyright education is to enhance students' awareness of copyright, fostering respect for others' copyrighted music and the protection of their own copyrighted music [23-24].

This paper addresses the issue of copyright knowledge learning effectiveness in the current music copyright education context by developing a research plan for optimizing copyright knowledge learning effectiveness based on the random forest algorithm. Under the guidance of relevant principles and theories, an evaluation indicator system for copyright knowledge learning effectiveness is designed, and through the weighting methods of the analytic hierarchy process and fuzzy comprehensive evaluation, the numerical quantification of evaluation indicators is achieved. Then, based on the theoretical knowledge of the random forest algorithm, the quantified indicator values are set as the input variables for the random forest algorithm, with the corresponding output variables being the evaluation optimization values, thereby completing the optimization of copyright knowledge learning effectiveness through the random forest algorithm. Finally, combined with the quantified indicator values, the algorithm's effectiveness in optimizing copyright knowledge learning outcomes is validated.

2. Exploring the effectiveness of copyright education

2.1. Problems with music copyright education

2.1.1. Copyright Ownership Disputes

Music education involves multiple stakeholders, including music education platforms, schools, teachers, users, and original copyright holders, in the process of curriculum development and implementation. However, the current Copyright Law fails to provide accurate and reasonable definitions of the relevant rights and interests of copyrighted works in music education. The unclear ownership of copyrights has become a widespread phenomenon in music education copyright infringement, leading to issues such as low learning effectiveness in music copyright education.

2.1.2. Platform Infringement

Through investigative analysis, it has been found that music education platforms often exploit their dominant market position to coerce teachers/users into signing copyright agreements that are unfairly tilted in favor of the platform. These agreements typically manifest in two primary forms:

(1) Unreasonable contract terms. Due to the nature of the internet and its technical characteristics, the agreements between music education platforms and teachers/users are typically presented as standard-form contracts. Teachers/users cannot choose the specific content of these standard-form contracts and must unconditionally accept them to gain access to the platform's services. Additionally, the platform's copyright agreements are often presented as hyperlinks or embedded within the terms of service, making it easy for teachers/users to overlook the content of the copyright agreement and sign it without fully understanding its terms.

(2) Music education platforms exploit their dominant position as copyright agreement drafters to reduce or even exempt themselves from copyright liability while imposing heavier copyright obligations on teachers/users. Through standard terms, the platform stipulates that teachers and users grant copyright content to the platform and requires them to guarantee the content is free of rights defects and assume liability for infringement, further exacerbating the poor learning outcomes of copyright knowledge in music copyright education.

2.1.3. Third-party infringement

Music education copyright infringers use technical means to obtain music education video files and related course materials, upload them to cloud storage platforms, and distribute them through free sharing on cloud storage platforms, Taobao, QQ, WeChat sales, and other channels. From piracy, storage, to sales, a music education piracy industry chain has already formed. Frequent copyright infringement activities directly harm the interests of copyright holders and online education platforms, disrupt the market order of music education, cause significant damage to the music education industry, and fail to enhance users' understanding of copyright knowledge.

The construction of an indicator system is a prerequisite for completing research on the optimization of random forest algorithm copyright knowledge learning effectiveness. After gaining a preliminary understanding of the issues that exist in music copyright education, the analytic hierarchy process and Delphi method were used to construct a copyright knowledge learning effectiveness evaluation indicator system. Details are shown below:

2.2. Construction of an evaluation indicator system

2.2.1. Construction Principles

There are numerous factors that influence the effectiveness of copyright knowledge learning, and it is essential to thoroughly consider the impact of various factors from different levels and perspectives on the effectiveness of copyright knowledge learning. To ensure the applicability of the copyright knowledge learning effectiveness evaluation indicator system and the accuracy and objectivity of the evaluation results, this paper adheres to the following principles in the selection of evaluation indicators:

(1) The principle of unifying systematicity and independence

When selecting indicators, factors that can comprehensively reflect the overall situation of copyright knowledge learning outcomes should be prioritized. Copyright knowledge learning is a complex process, so the selection of evaluation indicators and the construction of the evaluation indicator system should consider the systematic nature of the indicators. At the same time, each evaluation indicator should also have independence, with no overlap in content between indicators, and clear and distinct boundaries. In summary, the indicator system should achieve a unity of systematicity and independence, comprehensively and clearly reflecting copyright knowledge learning outcomes.

(2) Principle of combining quantitative and qualitative approaches

Assessment indicators should include both quantitative data collected from relevant literature and statistical data to ensure the accuracy of the indicators. At the same time, there should also be qualitative indicators that can objectively evaluate the effectiveness of copyright knowledge learning based on actual circumstances. When designing indicators, both qualitative and quantitative approaches should be adopted to strive for a more objective and scientific presentation of assessment results.

(3) Principle of balancing focus and comprehensiveness

Copyright protection is influenced by multiple factors, so the assessment indicator system must cover all areas affecting copyright learning. However, listing all factors without prioritizing them can result in an assessment lacking hierarchy, priority, and logic. Therefore, when selecting and constructing the assessment indicator system, indicators should be reasonably screened based on their importance to achieving copyright protection, ensuring the system highlights key areas while comprehensively reflecting issues.

2.2.2. Establishment of an evaluation indicator system

Based on the above theory, an evaluation index system for assessing the effectiveness of copyright knowledge learning in music copyright education was constructed. The evaluation index system is shown in Table 1. As can be seen from the table, the evaluation index system consists of four first-level indicators and 13 second-level indicators.

Table 1. Evaluation index system.

First-level indicator	Symbol	Secondary indicators	Symbol
Learning of legislative knowledge	X1	The number of music copyright legislations	X11
		The number of legislations related to the copyright protection of music education	X12
		The applicability of legal provisions	X13
Learning of judicial knowledge	X2	The annual case acceptance rate of music education copyright cases	X21
		Annual case closure rate of music education copyright cases	X22
		The average case closure time for music education copyright cases	X23
		The amount of copyright compensation for music education is greater than the amount of the lawsuit request	X24
Administrative knowledge learning	X3	The number of special rectification actions for music Copyrights	X31
		The number of cases investigated and dealt with regarding music education copyright	X32
		The amount of copyright investigation and punishment for music education	X33
Social knowledge learning	X4	Public awareness of copyright protection	X41
		The quantity of publicity and education on copyright protection in music education	X42
		Publicity methods for copyright protection in music education	X43

2.3. Quantification of evaluation indicator data

2.3.1. Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) involves decomposing the factors contributing to a complex problem into distinct components and organizing these components into hierarchical levels. Each level is then evaluated using predetermined criteria to construct a judgment matrix. In this study, the square root method was employed to calculate the maximum eigenvalue and its corresponding eigenvector of the matrix, thereby determining the weights of the criterion layers and the combined weights of the overall indicators. Finally, a comprehensive ranking of the hierarchical levels was conducted to derive the weights of different schemes and select the optimal solution. [25]. The specific steps of the Analytic Hierarchy Process (AHP) are as follows:

Step 1: Clarify the problem.

Step 2: Establish a hierarchical structural model. After thoroughly analyzing the problem at hand, the factors contained in the problem are divided into different levels, such as the objective level, criterion level, indicator level, scheme level, and measure level, and the hierarchical structure of the levels and the subordinate relationships between the factors are illustrated using a block diagram.

Step 3: Construct a comparison judgment matrix. The judgment matrix uses a specific element from the overall indicator layer as the evaluation criterion to conduct pairwise comparisons of elements in the sub-criterion layer to determine the matrix elements. The values of the matrix elements reflect people's perceptions of the relative importance of various indicators. Generally, a scale method using 1–9 and their reciprocals is adopted, as shown in Table 2.

Table 2. The criterion for judging relative importance.

Scale	Definition of judgment scale
1	The two elements are of equal importance compared with each other
3	When comparing the two elements, one is slightly more important than the other
5	When comparing the two elements, one is obviously more important than the other
7	Compared with the two elements, one element is strongly more important than the other
9	Compared with the two elements, one is extremely important than the other, 2,4,6 and 8 are between the intermediate values of the above two adjacent judgment scales

Step 4: Calculate the weights by first finding the maximum eigenvalue of the decision matrix and its corresponding eigenvector W , that is:

$$BW = \lambda_{\max} W \tag{1}$$

The components of W , $(W_1, W_2, ..., W_n)$, correspond to the relative importance of the n elements, i.e., the weight coefficients. There are two methods for calculating the weight values: the sum-product method and the square root method. This paper uses the square root method.

Sum-product method: Normalize each column of the judgment matrix. The formula is:

$$\overline{b_{ij}} = b_{ij} / \sum_{k=1}^{n} b_{kj} \, (i = 1, 2, ..., n) \tag{2}$$

For the judgment matrix normalized by column, sum by row:

$$\overline{W_i} = \sum_{j=1}^{n} \overline{b_{ij}} \, (i = 1, 2, ..., n) \tag{3}$$

Normalize vector $\overline{W} = [\overline{W_1}, \overline{W_2}, ..., \overline{W_n}]^T$:

$$W_i - \overline{W}_i / \sum_{i=1}^{n} \overline{W}_i (i = 1, 2, ..., n) \tag{4}$$

Then $W = [W_1, W_2, ..., W_n]^T$ can be approximated as the relative weight of each indicator to calculate the maximum characteristic root:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(BW)_i}{nW_i} \tag{5}$$

$(XW)_i$ denotes the i th component of vector XW .

Square root method: Calculate the product of each row element of the decision matrix:

$$M_i = \prod_{j=1}^{n} b_{ij} \, (i = 1, 1, ..., n) \tag{6}$$

Calculate the n th root of M_i , $\overline{W}_i = \sqrt[3]{M_i} \, (i - 1, 2, ..., n)$, and normalize the vector $\overline{W} = [\overline{W}_1, \overline{W}_2, ..., \overline{W}_n]^T$:

$$W_i - \overline{W_i} / \sum_{i=1}^{n} \overline{W_i} (i = 1, 2, ..., n) \tag{7}$$

Then $W = [W_1, W_2, ..., W_n]^T$ can be approximated as the relative weight of each indicator to calculate the maximum characteristic root:

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(XW)_i}{nW_i} \tag{8}$$

Step 5: Consistency check. Consistency indicator CI is:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{9}$$

Calculate the consistency ratio $CR = \frac{CI}{RI}$, where RI is the random consistency index of comparison matrices of different orders. For orders 1 and 2, RI is 0. For order 3, RI is 0.58. For order 4, RI is 0.9. For order 5, RI is 1.12. For order 6, RI is 1.24. For order 7, RI is 1.32. For order 8, RI is 1.41. For order 9, RI is 1.45. For order 10, RI is 1.49. When CR < 0.1, the judgment matrix is considered to have satisfactory consistency, and the calculated weights are acceptable.

Step 6: Hierarchical overall ranking. After calculating the weights of each level of indicators, starting from the overall objective level, the overall weights of each element for the system's overall objective level are determined, i.e., hierarchical overall ranking is performed.

Step 7: Consistency check of hierarchical total ranking. Similar to single-level ranking, a consistency check is required. When $CR < 0.10$, the hierarchical total ranking is considered to have passed the consistency check; otherwise, the judgment matrix must be adjusted until the hierarchical total ranking passes the consistency check.

2.3.2. Fuzzy comprehensive evaluation method

The basic idea of F comprehensive evaluation is to use the F linear transformation principle and the maximum membership principle to consider all factors related to the evaluated object and make a reasonable comprehensive evaluation.

There are three elements of comprehensive evaluation:

(1) Factor set: $U = \{u_1, u_2, u_3, ..., u_m\}$, where there are m factors related to the evaluated object.

(2) Judgment set: $V = \{v_1, v_2, v_3, \ldots, v_m\}$, where there are n possible judgments.

(3) Single-factor judgment, i.e., the evaluation of a single factor $u_i (i = 1, ..., m)$, yields a set F $(r_{i1}, ..., r_{in})$ on V , so it is an F mapping from U to V :

$$f : U \to \zeta(V) \tag{10}$$

$$u_i \to (r_{i1}, ..., r_{in}) \tag{11}$$

The mapping F can determine a f relation $R \in \mu_{mm}$, which becomes the evaluation matrix. It is:

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} \tag{12}$$

It is composed of the set F of all factor evaluations.

Since the importance of each factor may not be equal, it is necessary to weight each factor. Use U on F sets $A = \{a_1, a_2, a_3, ..., a_m\}$ to indicate the weight distribution of each factor, combine it with the evaluation matrix R , and obtain the comprehensive evaluation set $B = \{b_1, b_2, b_3, ..., b_n\}$, then:

$$A \circ B = B = \{b_1, b_2, b_3, ..., b_s\} \tag{13}$$

Among them:

$$A = \{a_1, a_2, a_3, ..., a_m\} \tag{14}$$

$$R = (r_{ij})_{m \times n}, r_{ij} \in [0,1] \tag{15}$$

$$b_j = \overset{m}{\underset{i=1}{\wedge}} (a_i \wedge r_{ij}), j = 1, 2, ..., n \tag{16}$$

It is a comprehensive evaluation of various factors. Finally, according to the principle of maximum membership degree, the grade (comment) v_j corresponding to the largest b_j in the comprehensive evaluation set B is selected as the result of the comprehensive evaluation. Thus, the comprehensive evaluation model (or model $M(i,v)$) is obtained.

The process of obtaining the comprehensive evaluation shows that when considering factor u_i alone, the evaluation of u_i has an affiliation degree $r_{ij}(j=1,2,...,n)$ with respect to comment v_j. The result obtained through the F relationship synthesis operation is:

$$b_j = \mathop{\vee}_{i=1}^{m}(a_i \wedge r_{ij}), j=1,2,...,n \tag{17}$$

When comprehensively considering various factors, the evaluation of u_i adjusts the membership degree of the comment v_j, i.e., the adjustment of r_{ij} when considering the influence degree a_i of u_i in the overall evaluation. Finally, the adjusted membership degrees are comprehensively processed through the F relationship synthesis operation to obtain a reasonable comprehensive evaluation result.

The steps for conducting a multi-level F comprehensive evaluation are as follows:

Step 1: Factor analysis, where the factors $U=\{u_1,u_2,u_3,...,u_n\}$ are categorized into the following classes based on certain attributes: s categories: $U_i=\{u_{i1},u_{i2},u_{i3},\ldots,u_{in}\}$, where $i=1,2,\ldots,s$, and they satisfy the following conditions:

(1) $n_1+n_2+\cdots+n_s=n$

(2) $U,UU_2\cup\cdots\cup U,=U$

(3) $(\forall i,j)(i\neq j\rightarrow U_i\cap U_i=\varnothing)$

Step 2: Establish the evaluation set $V=\{v_1,v_2,v_3,\ldots,v_p\}$.

Factor class weight set: If the weight of factor U_i in class i is $a_i(i=1,2,\cdots,s)$, then the factor class weight set is $A=\{a_1,a_2,a_3,...,a_i\}$; factor weight set: If factor a_q is the j th factor in class i, then the factor weight set is $A_i=\{a_{i1},a_{i2},a_{i3},...,a_{in_1}\}(i=1,2,...,s)$.

Step 4: Comprehensive evaluation at the first level

Comprehensive evaluation of each factor in each category is conducted. The single-factor evaluation matrix for comprehensive evaluation at the first level is as follows:

$$R=\begin{pmatrix} r_{11}^{(i)} & \cdots & r_{1p}^{(i)} \\ \vdots & \ddots & \vdots \\ r_{n_i1}^{(i)} & \cdots & r_{n_ip}^{(i)} \end{pmatrix} \tag{18}$$

In the comprehensive evaluation of layer F, the evaluation model $M(\wedge,\vee)$ is used. Then, the comprehensive evaluation matrix B_i of factor class i in F is:

$$\begin{aligned} B_i &= A_i \circ R_i \\ &= (a_{i1},a_{i2},...,a_{in_i}) \circ \begin{pmatrix} r_{11}^{(i)} & \cdots & r_{1p}^{(i)} \\ \vdots & \ddots & \vdots \\ r_{n_11}^{(i)} & \cdots & r_{n_ip}^{(i)} \end{pmatrix} \\ &= (b_{i1},b_{i2},...,b_{ip}) \end{aligned} \tag{19}$$

Step 5: Second-level comprehensive evaluation

First, generate a first-level F comprehensive evaluation matrix (or multi-level F comprehensive evaluation matrix) to obtain the single-factor class evaluation matrix R for the second-level F comprehensive evaluation:

$$R=\begin{bmatrix}B_1\\B_2\\\vdots\\B_s\end{bmatrix}=\begin{bmatrix}A_1\circ R_1\\A_2\circ R_2\\\vdots\\A_s\circ R_3\end{bmatrix}=\begin{bmatrix}b_{11}&\cdots&b_{1p}\\\vdots&\ddots&\vdots\\b_{31}&\cdots&b_{3p}\end{bmatrix}=(b_1,b_2,...,b_p) \tag{20}$$

In the second-level comprehensive evaluation, the F comprehensive evaluation model $M(\bullet,+)$ is used, so the second-level F comprehensive evaluation matrix B is:

$$B=A\times R=(a_1,a_2,...,a_s)\times\begin{bmatrix}b_{11}&\cdots&b_{1p}\\\vdots&\ddots&\vdots\\b_{s1}&\cdots&b_{sp}\end{bmatrix}=(b_1,b_2,...,b_p) \tag{21}$$

2.4. Optimizing copyright learning outcomes

2.4.1. Random Forest Algorithm

Random Forest (RF) is an ensemble learning model composed of a collection of decision tree classifiers, known for its excellent generalization and robustness. In Random Forest, the training set for each decision tree is randomly sampled from the original dataset using the bootstrap method. For node splitting in each decision tree, RF employs a random subspace selection method to randomly select attributes from the original attribute set. Subsequently, one of the following algorithms—the ID3 algorithm based on information gain, the C4.5 algorithm based on information gain rate, or the CART algorithm based on the Gini coefficient—is used as the node splitting rule for the decision tree. The best splitting attribute and splitting point are selected from the chosen attributes to generate the decision tree. Each decision tree is independent and does not influence others. Finally, the classification results of each tree are integrated using majority voting to obtain the predicted label for the test sample.

2.4.2. Specific Process

Input: Copyright knowledge learning effectiveness evaluation value (calculated using the hierarchical analysis algorithm and comprehensive fuzzy judgment method), number of decision trees s, number of attributes participating in splitting t, and test sample x.

Output: Optimized copyright knowledge learning effectiveness evaluation value of the test sample.

Step 1: Use the bootstrap sampling method with replacement to randomly sample from the copyright knowledge learning effectiveness evaluation values of the n samples, generating s datasets $D_i\left(i=1,2,3\cdots,s\right)$, where the number of samples in D_i is also n.

Step 2: Based on each D_i, train the decision tree model $h_i\left(x\right)$. During tree generation, randomly select t attributes from all m attributes to participate in node splitting ($t<m$, and t value is constant), and select one of the $ID3$ algorithm, $C4.5$ algorithm, or $CART$ algorithm as the node splitting rule to generate s decision trees.

Step 3: For the category $C\left(x\right)$ of the new input sample x, the majority voting mechanism integrates the prediction results of the s decision trees. The calculation formula for $C\left(x\right)$ is as follows:

$$C\left(x\right)=\arg\max_{r}\sum_{i=1}^{s}I\left(h_i\left(x\right)=r_j\right),i=1,2,\cdots,s,j=1,2,\cdots,c \tag{22}$$

Among them, $h_i\left(x\right)$ represents the optimization result of the i th decision tree, r_j denotes the j th indicator label, and $I\left(\cdot\right)$ is an indicator function such that when $h_i\left(x\right)=r_j$, $I=1$, otherwise $I=0$.

3. Empirical Analysis of the Learning Effectiveness of Copyright Knowledge

3.1. Quantitative analysis of evaluation indicator data

3.1.1. Analysis of assessment indicator weighting results

Based on the calculation steps of the analytic hierarchy process (AHP) and combined with the scaling method, expert survey scoring was used to establish judgment matrices for each level and item of the copyright knowledge learning effectiveness evaluation indicators. According to the scaling method, expert survey scoring was used to determine the importance relationships of the first-level indicators, as shown in Table 3.

Table 3. Expert Investigation Scoring sheet.

Hierarchy	Compare the two indicators before and after	Scale value
X	Comparison between X1 and X2	1/5
	Comparison between X1 and X3	1/2
	Comparison between X1 and X4	1/3
	Comparison between X2 and X3	2
	Comparison between X2 and X4	3
	Comparison between X3 and X4	5

Based on the basic calculation steps of the aforementioned analytic hierarchy process, experts scored the influencing factors of each level according to their experience, and the results of the matrix weight calculation are shown in Table 4.

Table 4. Judge the calculation result of the matrix weights.

X	X1	X2	X3	X4	Multiplication of row elements	The NTH power of the product of row elements	Weight normalization processing
X1	1	0.2	0.5	0.33	0.033	0.4262	0.0865
X2	5	1	2	3	30	2.3403	0.4748
X3	2	0.5	1	5	5	1.4953	0.3034
X4	3	0.33	0.2	1	0.198	0.6671	0.1353

Calculate the maximum eigenvalue of the decision matrix:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(A\omega)_i}{n\omega_i} = 4.133$$

Perform consistency checks and calculate CI

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{4.133-4}{3} = 0.0443$$

Given that $RI = 0.89$ and $CR = \dfrac{CI}{CR} = \dfrac{0.0443}{0.89} = 0.0498$ satisfy the consistency requirement (CR is less than 0.01).

Similarly, according to the 1-9 scale method, the importance relationships of other indicators are determined, and the expert survey scoring results are shown in Table 5.

Table 5. The expert investigation and scoring results.

Hierarchy	Compare the two indicators before and after	Scale value
X1	Comparison between X11 and X12	0.2
	Comparison between X11 and X13	0.25
	Comparison between X12 and X13	0.33
X2	Comparison between X21 and X22	0.33
	Comparison between X21 and X23	0.5
	Comparison between X21 and X14	0.33
	Comparison between X22 and X23	0.2
	Comparison between X22 and X24	0.25
	Comparison between X23 and X24	2
X3	Comparison between X31 and X32	0.25
	Comparison between X31 and X33	0.2
	Comparison between X32 and X33	0.5
X4	Comparison between X41 and X42	0.33
	Comparison between X41 and X43	0.33
	Comparison between X42 and X43	0.5

Based on the basic calculation steps of the aforementioned analytic hierarchy process, experts scored the influencing factors of each level according to their experience, and the results of the judgment matrix weight calculation are shown in Tables 6 to 9. After calculation, the CR values of the weights of all indicators were found to be less than 0.01, indicating that the judgment matrix meets the consistency requirements.

Table 6. Judge the calculation result of the matrix weights(X1).

X1	X11	X12	X13	Multiplication of row elements	The NTH power of the product of row elements	Weight normalization processing
X11	1	0.2	0.25	0.05	0.3684	0.0969
X12	5	1	0.33	1.65	1.1817	0.3078
X13	4	3	1	12	2.2894	0.5963

Table 7. Judge the calculation result of the matrix weights(X2).

X2	X21	X22	X23	X24	Multiplication of row elements	The NTH power of the product of row elements	Weight normalization processing
X21	1	0.33	0.5	0.33	0.0545	0.4831	0.1009
X22	3	1	0.2	0.25	0.15	0.6223	0.1301
X23	2	5	1	2	20	2.1147	0.4419
X24	3	4	0.5	1	6	1.5651	0.3271

Table 8. Judge the calculation result of the matrix weights(X3).

X3	X31	X32	X33	Multiplication of row elements	The NTH power of the product of row elements	Weight normalization processing
X31	1	0.25	0.2	0.05	0.3684	0.0974
X32	4	1	0.5	2	1.2599	0.3331
X33	5	2	1	10	2.1544	0.5695

Table 9. Judge the calculation result of the matrix weights(X4).

X4	X41	X42	X43	Multiplication of row elements	The NTH power of the product of row elements	Weight normalization processing
X41	1	0.33	0.33	0.1089	0.4775	0.1388
X42	3	1	0.5	1.5	1.1447	0.3328
X43	3	2	1	6	1.8171	0.5283

The consistency test for each judgment matrix in the above table shows that CR < 0.1, indicating a high level of consistency. Therefore, the consistency of the judgment matrices is considered acceptable. Since all consistency tests have been passed, the normalized feature vectors are the weight vectors for each indicator. The total weight for the learning effectiveness of copyright knowledge in music copyright education is calculated in a table. Based on the calculation results, the Rank function in Excel software is used to sort the results. The weight calculation results and their overall ranking are shown in Table 10 below. The results show that X11 (0.0084) < X41 (0.0188) < X12 (0.0266) < X31 (0.0296) < X42 (0.0450) < X21 (0.0479) <X13 (0.0516) <X22 (0.0618) <X43 (0.0715) <X32 (0.1011) <X24 (0.1553) <X33 (0.1728) <X23 (0.2098).

Table 10. Total ranking of weights.

Project	**X1**	**X2**	**X3**	**X4**	**Total weight**	**Overall sorting**
	0.0865	**0.4748**	**0.3034**	**0.1353**		
X11	0.0969				0.0084	13
X12	0.3078				0.0266	11
X13	0.5963				0.0516	7
X21		0.1009			0.0479	8
X22		0.1301			0.0618	6
X23		0.4419			0.2098	1
X24		0.3271			0.1553	3
X31			0.0974		0.0296	10
X32			0.3331		0.1011	4
X33			0.5695		0.1728	2
X41				0.1388	0.0188	12
X42				0.3328	0.0450	9
X43				0.5283	0.0715	5

3.1.2. Analysis of comprehensive assessment results

(1) Establish evaluation factors and a set of evaluation criteria. By hiring 15 experts to evaluate and score the copyright knowledge learning effectiveness evaluation index system, and then organizing and determining the evaluation values of each index, the evaluation scores for each index are shown in Table 11. Among them, U1 to U5 correspond to excellent, good, average, poor, and very poor, respectively, and are assigned values of 5, 4, 3, 2, and 1.

Table 11. Scoring values of various indicators.

First-level indicator	**Secondary indicators**	**U1**	**U2**	**U3**	**U4**	**U5**
X1	X11	5	3	2	2	3
	X12	3	7	2	2	1
	X13	5	1	2	4	3
X2	X21	3	2	4	3	3
	X22	4	3	3	1	4
	X23	3	5	2	2	3
	X24	3	3	3	3	3
X3	X31	5	4	3	1	2
	X32	3	6	2	1	3
	X33	4	6	2	2	1
X4	X41	2	6	1	4	2
	X42	4	1	4	2	4
	X43	4	5	2	1	3

(2) Determine the evaluation membership matrix. Based on Table 11, the scores for each indicator are normalized, and the normalization results are shown in Table 12. Determine the evaluation membership matrix. Based on the data in the table, we obtain:

$$R_{X1} = \begin{bmatrix} 0.3333 & 0.2 & 0.1333 & 0.1333 & 0.2 \\ 0.2 & 0.4667 & 0.1333 & 0.1333 & 0.0667 \\ 0.3333 & 0.0667 & 0.1333 & 0.2667 & 0.2 \end{bmatrix}$$

$$R_{X2}=\begin{bmatrix} 0.2 & 0.1333 & 0.2667 & 0.2 & 0.2 \\ 0.2667 & 0.2 & 0.2 & 0.0667 & 0.2667 \\ 0.2 & 0.3333 & 0.1333 & 0.1333 & 0.2 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}$$

$$R_{X3}=\begin{bmatrix} 0.3333 & 0.2667 & 0.2 & 0.0667 & 0.1333 \\ 0.2 & 0.4 & 0.1333 & 0.0667 & 0.1333 \\ 0.2667 & 0.4 & 0.1333 & 0.1333 & 0.0667 \end{bmatrix}$$

$$R_{X4}=\begin{bmatrix} 0.1333 & 0.4 & 0.0667 & 0.2667 & 0.1333 \\ 0.2667 & 0.0667 & 0.2667 & 0.1333 & 0.2667 \\ 0.2667 & 0.3333 & 0.1333 & 0.0667 & 0.02 \end{bmatrix}$$

Table 12. Normalize the processing result.

First-level indicator	**Secondary indicators**	**U1**	**U2**	**U3**	**U4**	**U5**
X1	X11	0.3333	0.2000	0.1333	0.1333	0.2000
	X12	0.2000	0.4667	0.1333	0.1333	0.0667
	X13	0.3333	0.0667	0.1333	0.2667	0.2000
X2	X21	0.2000	0.1333	0.2667	0.2000	0.2000
	X22	0.2667	0.2000	0.2000	0.0667	0.2667
	X23	0.2000	0.3333	0.1333	0.1333	0.2000
	X24	0.2000	0.2000	0.2000	0.2000	0.2000
X3	X31	0.3333	0.2667	0.2000	0.0667	0.1333
	X32	0.2000	0.4000	0.1333	0.0667	0.2000
	X33	0.2667	0.4000	0.1333	0.1333	0.0667
X4	X41	0.1333	0.4000	0.0667	0.2667	0.1333
	X42	0.2667	0.0667	0.2667	0.1333	0.2667
	X43	0.2667	0.3333	0.1333	0.0667	0.2000

(3) Weight sets for each secondary indicator factor

From the above evaluation indicator weighting, we can see that $W_X=(0.0865, 0.4748, 0.3034, 0.1353)$ and $W_{X1}=(0.0969, 0.3078, 0.5963)$, $W_{X2}=(0.1009, 0.1301, 0.4419, 0.3271)$, $W_{X3}=(0.0974, 0.3331, 0.5695)$, $W_{X4}=(0.1388, 0.3328, 0.5283)$, respectively, to conduct a comprehensive evaluation of each evaluation indicator. Specifically, as follows:

$$C_{X1}=W_{X1}\times R_{X1}=[0.2926, 0.2028, 0.1334, 0.2130, 0.1592]$$

$$C_{X2}=W_{X2}\times R_{X2}=[0.2087, 0.2522, 0.1773, 0.1532, 0.2087]$$

$$C_{X3}=W_{X3}\times R_{X3}=[0.2510, 0.3870, 0.1398, 0.1046, 0.1176]$$

$$C_{X3}=W_{X3}\times R_{X3}=[0.2482, 0.2538, 0.1684, 0.1166, 0.2129]$$

(4) Determine the fuzzy matrix. Calculate the comprehensive fuzzy evaluation matrix:

$$C=\left(C_{X1},C_{X2},C_{X3},C_{X4}\right)=\begin{bmatrix}0.2926 & 0.2028 & 0.1334 & 0.2130 & 0.1592\\0.2087 & 0.2522 & 0.1773 & 0.1532 & 0.2087\\0.2510 & 0.3870 & 0.1398 & 0.1046 & 0.1176\\0.2482 & 0.2538 & 0.1684 & 0.1166 & 0.2129\end{bmatrix}$$

Based on $W_X=\left(0.0865,0.4748,0.3034,0.1353\right)$, a comprehensive assessment of the learning outcomes of copyright knowledge in music copyright is conducted. Therefore, $X=W\times C=\left[0.2771,0.3354,0.1849,0.1566,0.1975\right]$, according to the established evaluation grades, the final assessment result is calculated to be 3.8724, i.e.:

$$\mathrm{Re}\,sult=\left(0.2771,0.3354,0.1849,0.1556,0.1975\right)\begin{pmatrix}5\\4\\3\\2\\1\end{pmatrix}=3.8724$$

3.2. Analysis of copyright learning effectiveness optimization

3.2.1. Analysis of Random Forest Optimization Effects

Based on Model $X=\left[0.2771,0.3354,0.1849,0.1566,0.1975\right]$, the Random Forest algorithm was applied to optimize the model. The analysis of the Random Forest optimization results is shown in Figure 1, where red, green, blue, cyan, and magenta represent U1, U2, U3, U4, and U5, respectively. As shown in the data in the figure, U1, U2, and U3 have seen an improvement in their evaluation scores, while U4 and U5 have shown a downward trend in their evaluation scores. The final evaluation result is 3.9365, an increase of 0.0641 compared to the pre-optimization value of 3.8724. This indicates that after the Random Forest optimization, the evaluation of copyright knowledge learning outcomes in music copyright has mostly shown excellent, good, and average results, the corresponding poor and very poor ratings have also been optimized to some extent, further enhancing users' copyright knowledge learning outcomes. This plays an important role in promoting and optimizing the high-quality development of music copyright education.

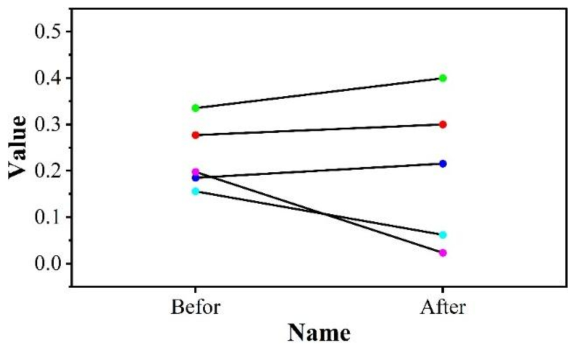

Figure 1. Random forest optimization effect.

3.2.2. Comparison and analysis of optimization effects

To further demonstrate the optimization effect of the RF (Random Forest) algorithm on the learning effectiveness of copyright knowledge in music copyright education, a comparative analysis of the optimization effects of DT (Decision Tree Algorithm), LSTM (Long Short-Term Memory Network), and LR (Logistic Regression) is shown in Figures 2 to 5. The optimization evaluation results for each algorithm were calculated, with values of 3.9365, 3.7213, 3.7323, and 3.7088, respectively. These results fully validate the optimization effect of the RF (Random Forest) algorithm on the effectiveness of copyright knowledge learning in music copyright education, thereby enhancing users' copyright knowledge levels.

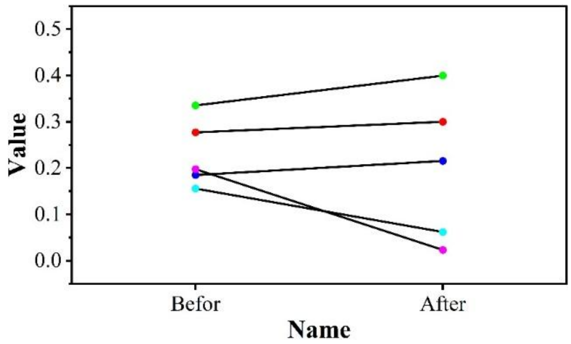

Figure 2. Optimization effect(RF)

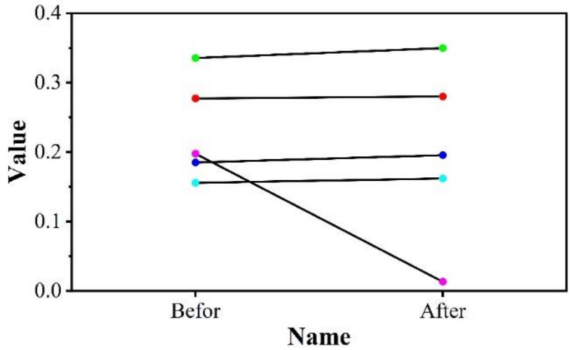

Figure 3. Optimization effect(DT)

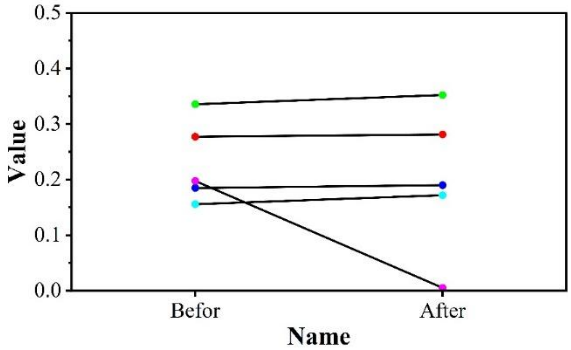

Figure 4. Optimization effect(LSTM)

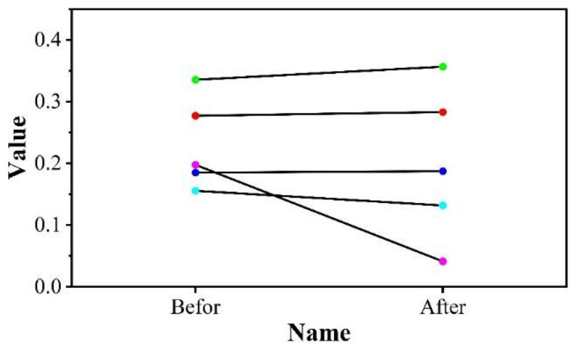

Figure 5. Optimization effect (LR)

4. Conclusion

Based on the issues identified in music copyright education, a performance evaluation indicator system for copyright knowledge learning outcomes was established. The indicators were quantified using the Analytic Hierarchy Process (AHP) and the Fuzzy Comprehensive Evaluation Algorithm. The quantified indicator values were used as input for the Random Forest Algorithm, with the optimized evaluation values set as the output. This process completed the design objective of an optimized model for evaluating copyright knowledge learning outcomes based on the Random Forest Algorithm. An empirical analysis of the research methodology was conducted using the corresponding indicator data. Under the optimization effects of the four algorithms, their corresponding optimization values were 3.9365, 3.7213, 3.7323, and 3.7088, respectively. Compared with DT (decision tree algorithm), LSTM (long short-term memory network), and LR (logistic regression), the RF (random forest) algorithm proposed in this paper demonstrates superiority in optimizing the learning effectiveness of copyright knowledge in music copyright education.

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