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Research Article

Online and Offline Mixed Teaching Mode Based on Multimedia Computer-Aided Music Lessons during the Epidemic

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In recent years, due to the repeated outbreak of the epidemic, the normal teaching of students has been affected, and many schools have conducted mixed online and offline teaching for students, so that students can carry out teaching activities anytime and anywhere without delaying course learning due to class suspension. This paper mainly studies the online and offline mixed teaching mode of multimedia computer-assisted music lessons under the epidemic situation and then selects two classes of students as experimental objects to carry out traditional online and offline teaching behaviors and online and offline teaching as the main, multimedia computer teaching as the main object, and compares the performance differences of the two classes in music courses to reflect the effect of multimedia computer-assisted online and offline teaching. This paper introduced the algorithm use of multimedia computer in detail and then applied it to teaching activities to improve the shortcomings of the existing teaching mode. In order to reflect the effect of the mixed teaching mode assisted by multimedia computer, this paper selected two classes of an experimental middle school to conduct experiments on their music class performance. Before the experiment, the algorithm was evaluated and tested, and the accuracy rate of the algorithm was 91.333%. By carrying out teaching activities in different modes and analyzing the data of the test results, it can be seen that the results of the teaching mode assisted by multimedia computer are much higher than the existing teaching mode. Compared with the traditional classroom learning, the scores of the first class in the music class under the two modes were 0.32 points and 4.74 points higher than those of the traditional classroom learning, and the second class was 0.25 points and 7.01 points higher, respectively. In terms of improvement rate, the improvement rates of Class 1 and Class 2 in the multimedia computer-assisted teaching mode were 6.593% and 9.432%, respectively, which indicated that multimedia computers played a positive role in the assisted mixed teaching mode.

1. Introduction

With the rapid development of information technology, people are not simply using computers to surf the Internet. In the current environment where the epidemic is still severe, the normal teaching activities of students in many countries have been seriously affected. Under this circumstance, many schools use a combination of online and offline teaching mode to conduct daily teaching for students, so that students can enjoy the normal teaching of the school at home. In the past online and offline teaching mode, the school only taught students through the online platform, the platform did not analyze the problems of the students, and the teachers could not understand the specific situation of the students and could only teach according to the prepreparation behavior. Although it did not delay the students' learning progress, the students' course performance did not improve much under this traditional model, and the learning effect was even lower than the traditional offline teaching. In this case, it is necessary to make full use of the powerful functions of multimedia computers, and let the computers take advantage of the advantages of personalized recommendation algorithms to improve the past online and offline teaching mode. Accurately locate the problems in the teaching activities, perform data conversion processing on the text information generated in the teaching activities, feed the students' problems back to the teacher in time, and then make corresponding changes to the curriculum according to the results. Finally, an experimental analysis of the improved teaching mode was carried out, and it was concluded that the online and offline mixed teaching mode assisted by multimedia computer has a positive effect on students' performance in music class. This conclusion also provided a reliable experimental basis for the subsequent changes in mixed teaching. Aiming at the shortcomings of the traditional online and offline mixed teaching mode, this paper mainly lets the multimedia computer learn the personalized recommendation algorithm and then processed the key information such as text information and digital information generated in the teaching activities according to the characteristics of the algorithm. Then, the processing results were fed back to the teaching teachers, and the remaining courses can be improved in time to improve the quality and efficiency of teaching. The application of this thinking provides certain ideas for changing the existing online and offline teaching mode.

In recent years, affected by the epidemic, not only schools have carried out online and offline teaching activities, but some companies have also carried out business training and other activities for employees through online and offline teaching. The wide application of online and offline teaching has aroused the interest of many scholars and conducted research on it. Through research and analysis, Wu found that the online and offline hybrid teaching mode can change the traditional classroom teaching mode. Its advantages can help to realize the transformation between languages and promote the understanding of Chinese culture by foreign students [1]. Xu believed that the effect of online and offline teaching on college computer courses is obvious. This mixed teaching model can bring a new teaching experience to boring computer courses and increase students' interest in boring coding courses [2]. Yen conducted an experimental analysis of online, offline, and online-offline mixed teaching for undergraduate child development courses to determine whether there are differences in students' course performance and satisfaction with different modes of teaching [3]. It can be seen from the research work of previous scholars that online and offline teaching can not only carry out teaching activities anytime and anywhere, but also improve students' learning. The interest in learning brings instructive significance to the development of the new teaching model.

The application of multimedia computer-assisted teaching breaks the shortcomings of traditional online and offline teaching, and provides certain convenience for daily teaching. The advantages of multimedia computers are not only reflected in students' teaching activities. Based on the wavelet transform theory, Zhu studied the speed of image compression and coding of multimedia computers in news technology and concluded that under this technology, image compression and coding are more convenient and faster [4]. Li analyzed the application of multimedia computer interactive education in preschool teacher training and found that multimedia computer interactive teaching can not only meet individual differences but also provide interactive functions, which greatly improves children's learning ability and interest [5]. Rachmadtullah studied the degree of effect of multimedia computer interaction in basic education. Through the analysis of students' learning materials, learning progress, and additional learning materials, it was known that the effect is positive and effective, and suitable for basic education activities [6]. Simarmata found that in daily teaching activities, the effectiveness of teaching activities is reduced due to the limitation of materials. Now with the help of multimedia computers, students can be broadened by playing videos and pictures to explain, and the teaching behaviors that could not be carried out before can be vividly displayed to students, so that students can have a deep understanding and improve their learning efficiency [7]. Sun studied the application of the multimedia computer teaching platform in the reform of university education. In the process of using multimedia computers, the teachers' teaching situation, the students' course learning situation, and other factors were fully considered, and the problems existing between the two were systematically dealt with, which greatly improve the quality of teaching [8]. It can be seen that multimedia computers can not only be used for interactive teaching, but also to open students' eyes and increase their interest in learning based on the rich teaching resources of multimedia computers, etc. The multi-functionality of multimedia computers provides new ideas for the change of the current teaching mode, and the advantages of multimedia computers can make up for the shortcomings of the current teaching and provide some help for the subsequent teaching reform.

The innovation of this paper is to combine multimedia computers with offline teaching, breaking the old teaching model, giving full play to the advantages of multimedia computers, implementing personalized recommendation algorithms for computer learning, allowing computers to analyze the course based on students' online and offline learning, and giving real-time feedback to the teaching teacher on the actual situation of students, and then the teacher makes improvements based on the results of the course analysis. The teacher then makes improvements to the shortcomings of the teaching process based on the results of the course analysis, and through the rich multimedia teaching resources and other features, the students are given targeted training, which not only improves the students' course performance but also stimulates their interest in learning, and this idea is proposed to provide certain guiding suggestions for the subsequent online and offline courses.

2. Personalized Recommendation Algorithm Theory

The traditional online and offline mixed teaching mode simply uses MOOC and SPOC and other network platforms to conduct daily teaching activities for students. This teaching mode has shortcomings such as low efficiency and inability to follow up students' learning progress in a timely manner. Now there are multimedia computers to improve the shortcomings of traditional online and offline mixed teaching. How does the multimedia computer realize it? In daily teaching activities, students' mastery of learning content and absorption efficiency are not the same. The traditional hybrid teaching mode can be improved through computer assistance. With the help of personalized recommendation algorithms, teachers can teach according to the actual situation of students, and teachers can also receive the personalized learning results of students fed back by the computer in time, so that teachers can improve the quality of teaching. Personalized recommendation algorithms can provide users with an accurate profile to guide product recommendations, and their product recommendation accuracy is better than other algorithms. Next, the related theory of personalized recommendation algorithm was introduced [9].

2.1. Collaborative Filtering Recommendation Algorithm. Implementing personalized recommendation for users is actually algorithmic recommendation, and the applicability of the algorithm determines whether it can recommend suitable content to users [10]. The main operation process is as follows: firstly, calculate the similarity measure between users or between items, and secondly calculate the similarity between users and items. Finally, find the K most similar items, and generalize the previous N most frequent items to all target objects in the same field.

The first thing needs to be considered is whether there is similarity between users. To put it simply, if the distance between the two is closer, the similarity is higher and vice versa [11]. Here are some common similarity functions:

(1) The similarity function based on the Pearson coefficient is to calculate the similarity $w_{u,v}$ between user *u* and user v, and its calculation is

$$w_{u,v} = \frac{\sum_{i\in I}\left(r_{u,i} - \overline{r_{u,v}}\right)\left(r_{v,i} - \overline{r_v}\right)}{\sqrt{\sum_{i\in I}\left(r_{u,i} - \overline{r_u}\right)^2 \sum_{i\in I}\left(r_{v,i} - \overline{r_v}\right)^2}}. \tag{1}$$

Among them, I is the product evaluated by users *u* and v at the same time, and $\overline{r_u}$ is the average score of all products evaluated by the u-th user.

(2) The similarity function based on cosine vector assumes that each evaluation of students is processed into a vector with its corresponding score, and then the similarity between students can be measured by calculating the cosine angle between these vectors. Assuming that a matrix *R* of m × n is used to measure students, then the cosine value of the n-dimensional vector corresponding to the i-th row and the j-th row in this matrix can be calculated, and this value can be expressed as the similarity between students. The range of similarity intervals for cosine vectors is [-1, 1]. The calculation is

$$w_{i,j} = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \bullet \vec{j}}{\|\vec{i}\| * \|\vec{j}\|}. \tag{2}$$

Among them, "•" represents the inner product of two vectors. In other words, if vector $\vec{X} = \{x_1, x_2, \ldots, x_n\}$, vector $\vec{Y} = \{y_1, y_2, \ldots, y_n\}$, then (3) is the cosine similarity between vectors $\vec{X}$ and $\vec{Y}$:

$$w_{X,Y} = \frac{x_1 x_2 \ldots x_n + y_1 y_2 \ldots y_m}{\sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}\sqrt{y_1^2 + y_2^2 + \ldots + y_n^2}}. \tag{3}$$

2.2. Algorithms Based on Content Recommendation. Content-based recommendation algorithms are good at overcoming sparsity and cold-start problems, and are good at interpreting recommendation results, while having high algorithm execution efficiency. The specific operation is to first extract the object features, and the extracted features are enough to describe the object and then record the user's usual preferences to generate a specific descriptive file. Finally, calculate the similarity between the user's real hobby object and the recommended object, and then recommend content according to the similarity [12].

When constructing the recommended object model, it is necessary to first evaluate the frequency of a certain keyword (the description of object feature extraction) appearing in the recommended object, which is expressed by importance here, and the calculation is

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}. \tag{4}$$

In (4), $n_{i,j}$ is the number of times the keyword appears in the recommended object d_j, and $\sum_k n_{k,j}$ is the sum of all words in the recommended object.

$$i\,df_i = \log \frac{|D|}{\left|\left\{j\colon t_i \in d_j\right\}\right|}. \tag{5}$$

In (5), t_i represents the inverse document frequency, |D| represents the total number of recommended objects in the corpus, and $\left|\left\{j\colon t_i \in d_j\right\}\right|$ represents the number of recommended objects containing keyword t_i.

In order to judge whether the recommended object meets the user's expectation, the utility function is used to calculate and explain it. The specific representation is

$$\mu(c,j) = \frac{\sum_{i=1}^{P} w_{i,c} w_{i,j}}{\sqrt{\sum_{i=1}^{P} w_{i,c}^2}\sqrt{\sum_{i=1}^{P} w_{i,j}^2}}. \tag{6}$$

In (6), P is the number of keywords. The smaller the value of $\mu(c,j)$, the better the recommended object meets the user's ideal expectations.

3. Implementation Process of the Algorithm

3.1. User Features. User features are generally divided into attribute features and behavioral features [13]. The content of personalized recommendation for users depends on the accuracy of user characteristic information. The specific user characteristics-related content is shown in Figure 1.

Different users have corresponding characteristic information. The recommendation system collected and then mined information according to this characteristic information, analyzed the favorite preferences of different users, timely pushed personalized content to users, and

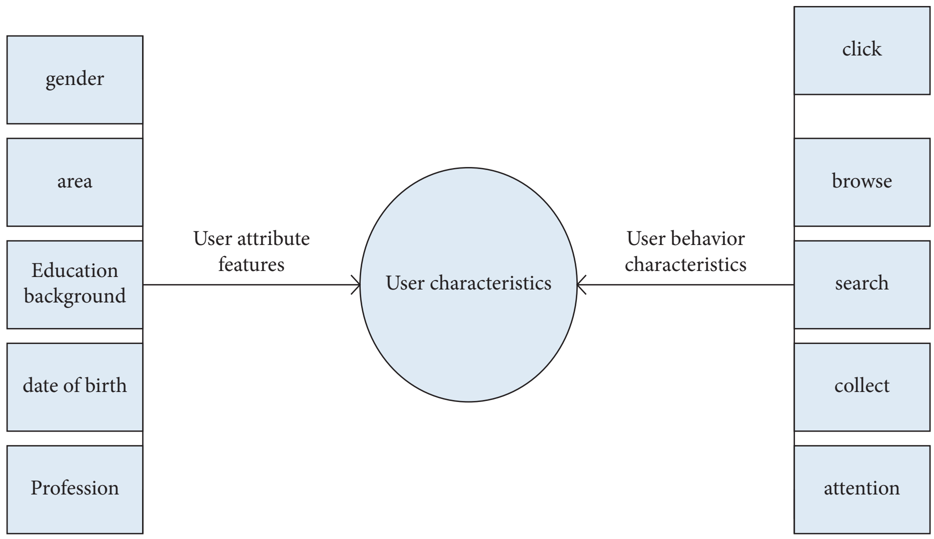

Figure 1: User feature classification.

met their needs. It can be seen that the extraction of feature information plays a crucial role in personalized service [14]. The source of user characteristic information is shown in Table 1.

The attribute characteristics of the user are generally the information registration of the user when the account is registered. This basic information is highly accurate and has obvious dominant characteristics representing the user, which is convenient for the system to identify and analyze. The user's behavioral characteristics mainly include the user's browsing, clicks, comments, and other related information, and this part of the information includes the user's favorite preference. However, this part of the information is both explicit and implicit. Explicit information can directly derive user needs, but implicit information needs to be studied and analyzed with the help of corresponding algorithms to obtain useful information for users. For example, when a student registers for an account, the account will have information such as the exact course name and course content, and not only that, but when a student is studying online, the videos they repeatedly watch or the questions they ask during the course will reflect some information about the course that is relevant to them.

Table 1: User feature source.

User characteristics	Source
Attribute feature	Registration message
Favorite feature	Click, browse, bookmark
Active login features	Purchase of related courses
Social characteristics	Evaluated by teachers

3.2. Labels. When students conduct online and offline learning, a large amount of data will be generated in the learning process. The information and data are highly free and unconstrained. The occurrence of this phenomenon will bring difficulties to the subsequent system analysis work, and it is difficult to extract object features from this complex text information. Information is standardized by means of abstract symbols such as numbers or characters, mainly because computers can process these abstract symbols more accurately and conveniently than, for example, verbal texts. Therefore, in order to better reflect the effect of multimedia computer assistance on online and offline teaching, it is necessary to standardize these text information data before the experiment, so as to facilitate the feature extraction of the system, and to achieve the enhancement effect of multimedia computer assistance [15]. For example, Zhang San is a second-year student majoring in music education at xx University, majoring in music literacy courses such as sheet music reading, sight-reading, listening, rhythm, harmony, writing, music appreciation, and music history, then the key information related to Zhang San is can be extracted from these texts.

When students conduct online and offline learning, the generated text information data may appear to be marked by users with one or more tags. The following images can be used to describe the relationship composition as shown in Figure 2.

Although multimedia computers cannot directly recognize and understand the semantics of tags like the human brain, according to Figure 2, the meaning of tags can be reflected from the marked course content. In order to better understand the standardization of labels, some concepts are now defined to facilitate subsequent work.

Definition 1. Label standardization: the process of mapping students' custom labels to semantic labels that can be recognized by the system.

Definition 2. Standard tags: tags with clear semantics and recognized by everyone, there is no correlation between each tag, and all tags form a tag set.

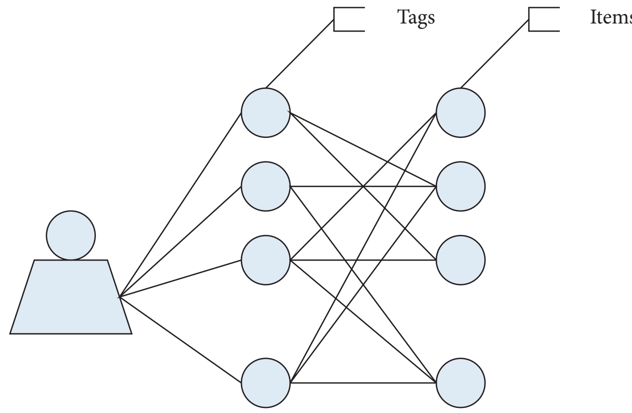

Figure 2: Relationship between labels and courses.

Definition 3. Word co-occurrence rate: it is assumed that during the online and offline learning process, the frequency of a word occurs repeatedly in each sentence, such as comments or active questions.

However, there will be semantic ambiguity in the process of label standardization. To solve this problem, three improvement methods were proposed: the first is tag matching, which matches and analyzes student-defined tags and tag sets; the second is to standardize words with high word co-occurrence rates; the third is to standardize tags with similar similarity. The combined use of these three methods can greatly improve the accuracy and work efficiency that cannot be standardized due to unclear semantics. The label standardization process is shown in Figure 3.

3.3. Operation Process of Two Kinds of Label Standardization

3.3.1. Label Standardization Based on Attribute Co-Occurrence Rate. When students are learning online and offline, their custom labels may have labeling errors. At this time, it is necessary to use the label standardization of the attribute co-occurrence rate to perform corresponding operations. By using the commonality of all resource objects in a marked set to express the true meaning of the label, combined with Definition 3, it can be seen that the condition that this attribute value satisfies is that the co-occurrence rate of the attribute value in this label set is 100% [16], and its calculation process is as follows:

Assume that the label to be standardized is t, resource set $P_t = \{p_1, p_2, \ldots p_l\}$ marked by t, and a certain resource $p_k = \{p_{k_1}, p_{k_2}, \ldots p_{k_n}\}$, $1 \leq k \leq l$, and $p_{k_i} (1 \leq i \leq n)$ are the attribute values of the i-th attribute of the resource. Then, the label normalization process based on attribute co-occurrence rate of label t is described as follows:

Now perform co-occurrence analysis on the resources marked in P; if $p_{1_i} = p_{2_i} = \ldots = p_{k_i} = \ldots = p_{l_i} = 1$, then take p_{k_i} as the standard label of all resources in this set; if $p_{k_i} \neq 1$, treat this p_{k_i} as a new standard tag and import it into the standard tag library.

3.3.2. Cluster-Based Label Normalization. Clustering plays an important role in the data mining process. Simply put, clustering is to classify several similar objects into clusters. Each cluster is independent, and there is a similarity or correlation between objects within a cluster [17]. In the clustering process of label standardization, this theory is also used for research and analysis.

In the usual research process, similarity is generally used to measure the similarity between two objects. But this is only studied based on numeric vectors, and this calculation method is not applicable when analyzing between words in the text. Therefore, used the method based on MI to calculate the similarity between different labels. MI is an evaluation criterion of information measurement. In short, it is to describe the value of Y that reflects the amount of information of X [18]. Assuming discrete random variables, then the expression is

$$I(X;Y) = H(X) - H(X \mid Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}. \quad (7)$$

In (7), $H(X)$ is the entropy of the random variable X, and $H(X \mid Y)$ is the conditional entropy of the random variable X given the random variable Y. The expressions of the two are

$$H(X \mid Y) = -\sum_{x \in X} \sum_{y \in Y} p(x,y) \log p(x \mid y). \quad (8)$$

The mutual information $I(t_i, t_j)$ and entropy $H(t_i)$ of labels t_i and t_j are calculated as

$$H(t_i) = -p(t_i) \log p(t_i). \quad (9)$$

Theoretically speaking, the larger the value of mutual information, the greater the correlation between the two labels; if t_i and t_j are related, $I(t_i, t_j) > 0$; otherwise $I(t_i, t_j) = 0$ [19]. That is to say, the value of mutual information can be used to represent the similarity of labels. In order to prevent the value from exceeding the theoretical range, it is normalized before comparison [20]. The similarity between those two labels is expressed as

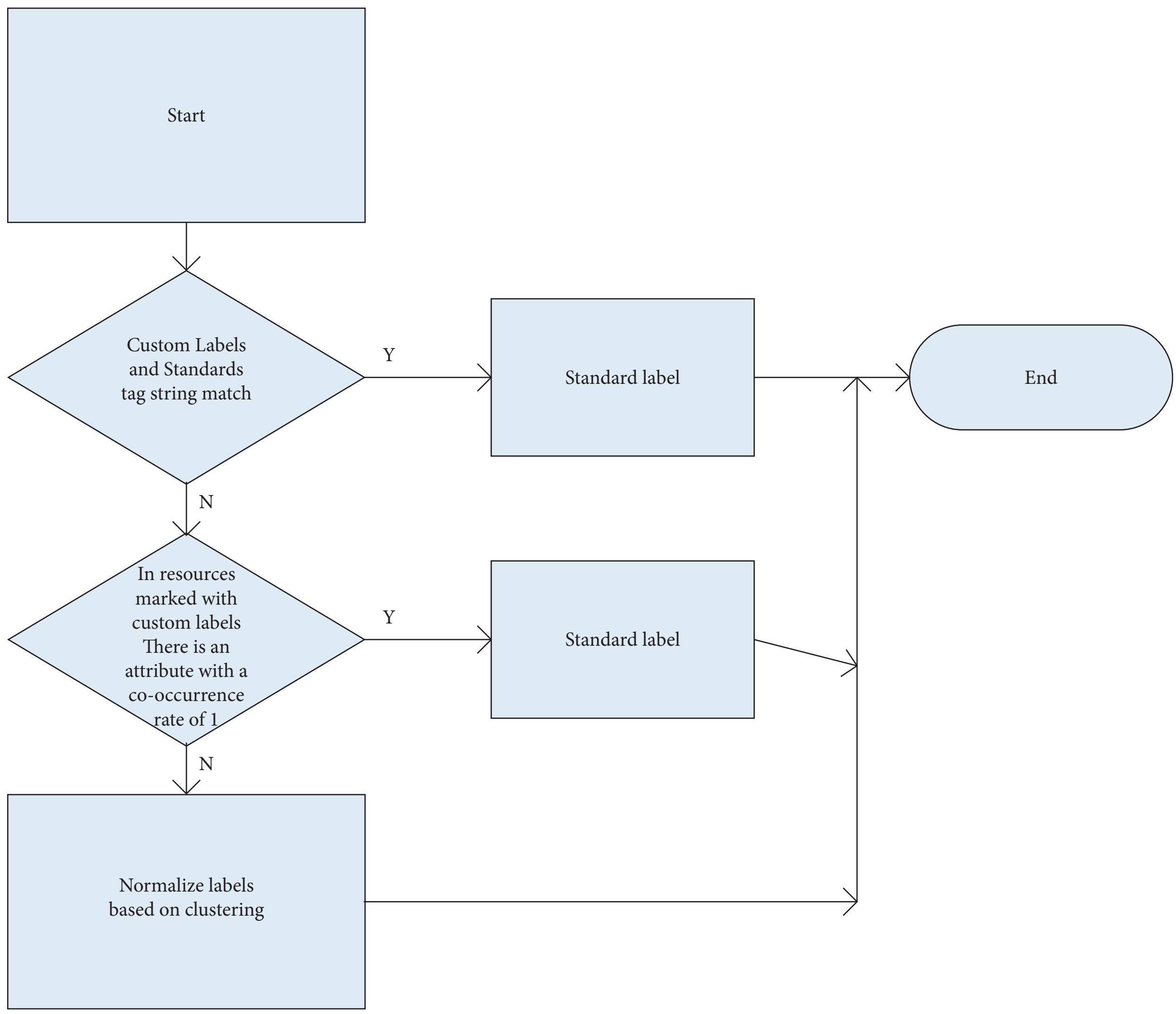

Figure 3: Label standardization process.

$$r_{i,j} = \frac{I(t_i, t_j)}{H(t_i) + H(t_j)/2}. \tag{10}$$

Among them, when $t_i = t_j$ and $r_{i,j} = 1$, there is a correlation between t_i and t_j and the two are completely correlated; when $t_i \neq t_j$ and $r_{i,j} = 0$, there is no correlation between t_i and t_j; in other cases, the value of $r_{i,j}$ is on the interval $[0, 1]$.

After analyzing and studying the similarity of labels, the next step is to cluster the labels on the basis of MI.

The clustering process of the personalized recommendation algorithm is similar to other clustering processes. It first determines a cluster center, that is, a standard label, and then calculates the distance between other labels and this standard label. Here, the size of the similarity was used to replace the size of the distance, the other tags with high similarity to the standard tag were grouped into a data set until the similarity between the remaining tags, the standard tag was less than a given value, and then the clustering process ends. Finally, the remaining labels were clustered with each other to obtain a new standard label, the new standard label was incorporated into the standard label data set, and the above operations were repeated until all custom labels complete the clustering operation. (11) is the definition of the similarity matrix R of labels:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \dots & \dots & \dots & \dots \\ r_{m} & r_{m2} & \dots & r_{mn} \end{bmatrix} = (r_{ij})_{m\times n}. \tag{11}$$

Among them, n is the number of standard signatures, m is the number of custom labels, and $r_{i,j}$ is the label similarity.

The implementation process of the MI algorithm is as follows:

Assuming that there is a standard label set of $T_S = \{t_{s1}, t_{s2}, \dots, t_{sn}\}$, other labels are represented by $T_P = \{t_{p1}, t_{p2}, \dots, t_{pm}\}$, and δ is used to represent the above given value and then operate the following:

(i) Operation 1: Take the label in T_S as the cluster center, and then calculate the similarity of all elements in the two sets according to (10).

(ii) Operation 2: Calculate the similarity matrix R of the tags according to (11).

(iii) Operation 3: Select the largest element r_{ij} in the calculated matrix R. If it is $r_{ij} \geq \delta$, then aggregate label t_{pi} into the class centered on label t_{sj}, and then delete the i-th row of R to obtain a $(m-l) * n$-dimensional matrix.

(iv) Operation 4: Repeat the steps of Operation 3 for the new matrix obtained in Operation 3. When the value of the largest element in the finally obtained matrix is less than the given value, the clustering process is terminated. The clusters obtained in the above process are classified into a set $C_1 = (c_1, c_2, \ldots, c_n)$, in which the cluster center of the standard label t_{si} $(1 \leq i \leq n)$ can be represented by c_i.

(v) Operation 5: Cluster the labels with the remaining similarity less than the given value again, then reconstruct the standard labels, and then perform the steps of Operations 1 and 2 to obtain a new matrix. Find the maximum value of the main diagonal of this matrix, finally repeat the process of Operations 3 and 4, and finally form a new cluster set $D_1 = (d_1, d_2, \ldots, d_n)$.

The finally obtained clustering result expression is

$$M = C_1 + D_1 = \{c_1, c_2, \ldots, c_n, d_1, \ldots, d_n\}. \tag{12}$$

It can be seen that the labels in each class form a mapping relationship with the standard labels of the class, and the custom labels that fail to cluster use themselves as the standard labels. The above two methods were used in combination to make up for each other's deficiencies and improve the accuracy of standardization. The attribute co-occurrence rate can make up for the problems of similar labels and too many labels in the clustering process when standardizing labels. The combination of the two improved the operating speed and accuracy of the system.

4. Experiments on Label Normalization Algorithms

4.1. Data Selection and Algorithm Evaluation Criteria

4.1.1. Experimental Data. This paper collects 1,000 comment records of 10 movies from 100 users on the Douban platform. In this data set, movies were divided into 8 categories, namely, action, adventure, animation, logical, truth, funny, thriller, and horror. During the experiment, the movie-related plot category, the main actor's preference for participating in the film, and the movie's tidbits were used as the labels of the movie. According to the algorithm, the tags of 100 users' comments are standardized, then compared and analyzed according to the processing results and the standard tags, and then combined with the evaluation results of the audience. In the process of processing, in order to form a comparison, 70% of the selected data set was used as the training set, and the remaining 30% was used as the test set. There was no correlation between the two data sets and both data sets contain the normalized results of all user and review labels.

4.1.2. Evaluation Criteria. In order to test the performance of the above algorithms, the corresponding evaluation criteria should be established. In this experiment, P@N (accuracy rate) was selected as the standard to measure the accuracy of the prediction results, and its calculation is

$$P@N = \frac{N_{max}}{N}. \tag{13}$$

In (13), N_{max} is #relevant items in top N items.

4.2. Experimental Results. In order to verify the advantages of the above algorithms, the slope one algorithm (method 1), the recommendation algorithm based on association rules (method 2), and the personalized recommendation algorithm (method 3) were selected for comparative analysis. The information data in the above data sets were randomly divided into 9 groups, then each data set was analyzed separately using the above algorithm, then the accuracy was compared according to the calculation, and the experimental results are shown in Table 2.

Then, the results of Table 2 were analyzed graphically, as shown in Figure 4.

As can be seen from Figure 4, the personalized recommendation algorithm had a higher accuracy of label standardization than the other two algorithms. Now calculate the mean of the data, and the result is shown in Figure 5 (three decimal places are reserved for the mean value).

Combining Figures 4 and 5, it can be seen that the accuracy of the personalized recommendation algorithm was higher than that of the other two algorithms in the 9 experimental data sets. After the average calculation of the 9 data results, the accuracy of the personalized recommendation algorithm was obtained. The rates were 3.444% and 4.222% higher than the other two algorithms, respectively, indicating that the personalized recommendation algorithm is effective in standardizing labels.

5. Multimedia Computer-Aided Music Class Online and Offline Mixed Teaching Mode

Based on the above experimental verification of the personalization algorithm, it was concluded that the personalized recommendation algorithm is better than other algorithms in terms of standardization of textual information and related content recommendations. After the matching was completed, the students' music course learning situation was fed back to the teacher in real time through computer analysis, so that the teacher could improve the teaching content based on the results and then use the rich teaching resources of multimedia computers to

Table 2: Accuracy data of different methods.

	Method 1	Method 2	Method 3
Group 1	87	86	90
Group 2	91	89	92
Group 3	89	86	93
Group 4	85	85	89
Group 5	96	95	98
Group 6	83	83	89
Group 7	79	83	88
Group 8	91	90	92
Group 9	90	87	91

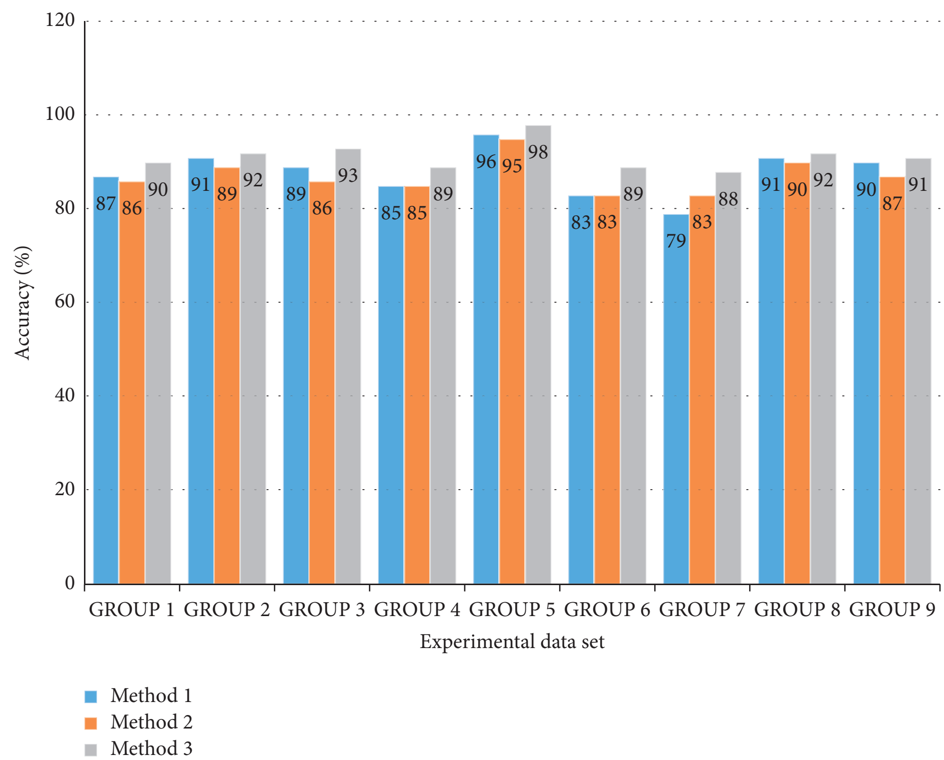

Figure 4: Accuracy data chart of different methods.

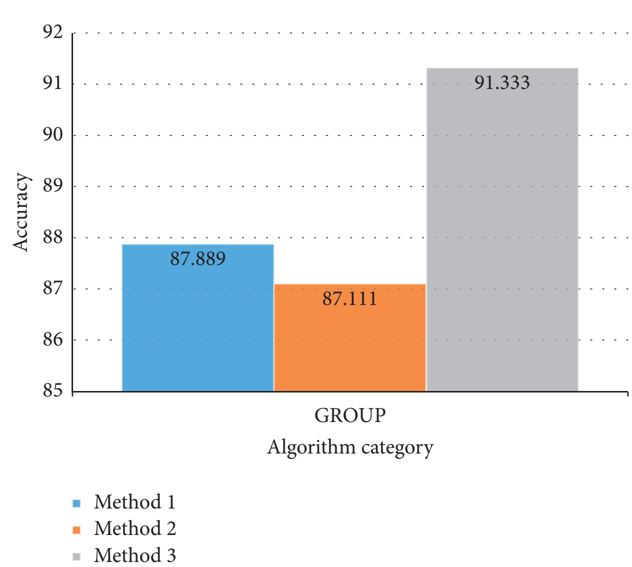

Figure 5: Average accuracy comparison chart.

teach students in a mixed way. In order to better reflect the acceptance rate, this paper mainly conducts a postlesson quiz on students to study and analyze the results.

5.1. Experimental Subjects and Methods. The research objects are two ordinary classes of grade 20 in a selected experimental middle school, taking the test scores of the music class as the research object. Before the experiment, the students in the two classes who participated in the experiment were checked whether they were interested in music lessons, and whether there was a large fluctuation in the scores of the music lessons before. After relevant investigations, it was found that there was no significant difference between the two classes, which met the basic conditions of this experiment. In this experiment, the number of students in the two classes is 45, of which the first class is the control group, and the second class is the experimental group.

During the experiment, it is necessary to clarify the experimental variables and other irrelevant variables in the experimental process. The irrelevant variables are the learning pace and receptivity of each student, etc. The independent variables of this paper are the traditional online and offline mixed teaching mode and the multimedia computer-assisted online and offline mixed teaching mode. Class one uses traditional online and offline mixed teaching, and the second class uses multimedia computer-assisted online and offline mixed teaching. The dependent variable is the students' test scores after completing the teaching activities of the music class.

5.2. Experimental Data. Before the experiment, the two classes should be tested on the course performance (the results of this experiment are the test results of traditional offline teaching) to ensure that the indicators of the two classes are at the same level. Only the conclusions drawn in this way are true and valid.

Use SPSS to process and analyze the grade data of the two classes, and the results are shown in Tables 3 and 4 (the full score is 100 points).

As can be seen from Table 4, the average score of the pre-experiment music class of the general class 1 was 72.21 points, the average score of the music class of the general class 2 was 74.56 points, and the average score of the second class was 2.35 points higher than that of the first class. In the comparative analysis of the standard deviation of the two classes, it was found that the standard deviation of the second class was smaller than that of the first class, which indicated that the grades of the second class students are relatively concentrated.

Next, a t-test is performed on the two classes, and the test results are shown in Table 5.

As can be seen from Table 5, the t-test is performed on the scores of the ordinary Class 1 and Class 2 before the experiment. In the case of equal variances, $p = 0.094 > 0.05$; in the case of different variances, $p = 0.093 > 0.05$. It shows that no matter whether the variances are equal or not, the difference between the two classes is not significant; that is, the average grades of the two classes are the same, which means that the two classes can be analyzed experimentally.

In order to ensure the validity of the experiment, the average of the mid-term scores of the two classes was taken as the reference value (the average is the average of all the scores of the two classes and the scores are in a stable state, not subject to sharp fluctuations due to distracting factors), the reference scores are the scores obtained from the tests conducted in the traditional offline teaching mode, and the scores of the music courses in the different teaching modes were compared and analyzed after the experiment. After conducting two kinds of teaching experiments in music class, the students in the two classes were tested for course performance, and then the obtained scores were analyzed by SPSS. The results obtained are shown in Tables 6 and 7.

As can be seen from Table 6, the average scores of the two classes after the two modes of teaching were 76.67 and 81.32, respectively, and the average score of the second class was 4.65 points higher than that of the first class. It showed that the online and offline mixed teaching mode assisted by multimedia computer is more effective than the traditional online and offline teaching, which is conducive to improving students' performance. Not only that, the standard deviation of the average scores of the two classes was smaller than the previous test data, which made the scores of the two classes relatively concentrated, indicating that the mixed teaching mode assisted by multimedia computers is reliable.

Table 7 shows a t-test for the scores of the two classes after the test. In the case of equal and unequal variances, the p value is less than 0.05, indicating that the difference between the two samples is significant. That is to say, there is a significant difference in the scores of ordinary classes 1 and 2 after the conventional online and offline mixed teaching and the online and offline mixed teaching assisted by multimedia computers. The average grades of the students in the second class have improved more than the average grades of the first class, which showed that the multimedia computer-aided teaching has a positive effect on online and offline mixed teaching activities.

In order to better reflect the effect of multimedia computer-aided online and offline mixed teaching, this paper, respectively, analyzes the performance of traditional teaching music class in nononline and offline teaching mode (experimental group 1), the traditional online and offline teaching music class performance (experimental group 2), and the results of multimedia computer-assisted online and offline teaching music class (experimental group 3). The experimental data results are shown in Figure 6 (the average scores are taken, respectively).

In Figure 6, it can be seen intuitively that after adopting different teaching modes for the music lessons of the two classes, their scores were improved compared with the traditional offline teaching. Among them, the music class scores of the first class were 0.32 points and 4.74 points higher than the traditional offline teaching scores under the two modes, and the music class scores of the second class were 0.25 points and 7.01 points higher than the traditional offline teaching scores, respectively. It showed that in the two

Table 3: The operating standard of the group experiment.

Class	Test subject	Pre-experimental state	Experimental factor	Experimental operation	Post-test status	Experimental results
Experimental class	A1	B1	C1	B1Q1	B1′	$D1 = B1'$-B1
Control class	A2	B2	C2	B2Q2	B2′	$D2 = D1'$-D1
Condition	A1 = A2		C1 ≠ C2			
	Result		C = C1–C2			

Table 4: Statistics of the basic situation group in the pretest for the first and second shifts.

	Pretest scores	
Class	1	2
Average value	72.21	74.56
Standard deviation	6.178	5.415
Standard error of the mean	0.932	0.835

Table 5: *T*-test.

			Assuming equal variances	Assuming unequal variances
Levene test for variance equation		F	1.32	
		Sig.	0.254	
		t	−1.692	−1.698
		df	84	83.398
t-test for the mean equation		Sig.(bilateral)	0.094	0.093
		Mean difference	−2.124	−2.124
		Standard error value	1.255	1.251
	95% confidence interval for difference	Lower limit	−4.621	-4.613
		Upper limit	0.372	0.364

Table 6: Postexperiment results.

	Postexperiment results	
Class	1	2
Average value	76.67	81.32
Standard deviation	5.814	5.013
Standard error of the mean	1.096	1.387

Table 7: Postexperiment *t*-test.

			Assuming equal variances	Assuming unequal variances
Levene test for variance equation		F	4.503	
		Sig.	0.038	
		t	−2.366	−2.361
		df	83	78.356
t-test for the mean equation		Sig.(bilateral)	0.02	0.21
		Mean difference	−4.175	−4.175
		Standard error value	1.762	1.765
	95% confidence interval for difference	Lower limit	−7.688	−7.698
		Upper limit	−0.668	−0.658

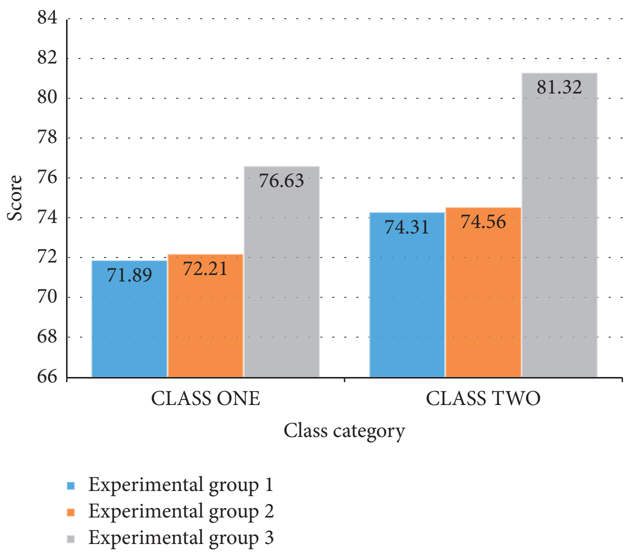

Figure 6: Comparison chart of scores before and after the experiment.

Figure 7: The graph of the improvement rate of the grades of the two classes.

classes under the multimedia computer-assisted teaching mode, the students' performance in music class has been improved.

In order to better reflect the improvement of grades, the improvement rate on the basis of the original data is calculated, and the results obtained are shown in Figure 7 (using the grades under the traditional teaching mode as the basic data).

As can be seen from Figure 7, the improvement rates of the music class scores of the first and second classes under the traditional online and offline mixed teaching were 0.445% and 0.336%, respectively, and the increase is not large; the improvement rate of music class performance in the online and offline mixed teaching mode assisted by multimedia computer is 6.593% and 9.432%, respectively, and the increase is far greater than that of the traditional online and offline mixed teaching mode. In short, the increase is 14.8 and 28.1 times the original, which indicated that the effect of online and offline mixed teaching of music lessons based on multimedia computer assistance is significant.

6. Conclusion

In recent years, many people have completed their learning tasks through online and offline teaching. The application of online and offline teaching mode allows people to carry out learning activities anywhere and anytime, providing people with great convenience. This paper mainly conducted auxiliary research on online and offline mixed teaching based on multimedia computers. In the research process, two classes of an experimental middle school are selected to conduct a comparative analysis of the changes in music class performance before and after the experiment. Before the experiment, the accuracy of the algorithm was tested experimentally, and it was concluded that the algorithm was effective; then, two classes were taught in different modes of teaching activities, and after the teaching activities were completed, curriculum tests were conducted. Then, the results of the test were researched and analyzed, and it was concluded that the multimedia computer-assisted education model has a positive effect on the existing teaching model. The main work of this paper can be divided into three points.

6.1. Theoretical Introduction to Algorithms in Multimedia Computers. This paper mainly applied the personalized recommendation algorithm to the multimedia computer. First, the content recommendation algorithm and the collaborative filtering algorithm of the personalized recommendation algorithm were introduced theoretically, and the implementation process of the algorithm was described accordingly.

6.2. Test of Personalized Recommendation Algorithm. This paper mainly used the personalized recommendation algorithm to improve the online and offline mixed mode teaching. Before the experiment, the accuracy of the algorithm needed to be tested to ensure that the algorithm can quickly and accurately judge and analyze the information in the subsequent process.

6.3. Multimedia Computer-Aided Online and Offline Mode Analysis. This section focuses on the experimental comparative analysis of traditional offline, traditional online, and multimedia computer-assisted online and offline teaching. Students in two classes are studied in different teaching modes, then the comparative analysis of teaching modes is based on the results of music course performance tests, and it is concluded that the multimedia computer-assisted online and offline hybrid teaching mode is superior to other teaching modes.

Due to the influence of the experimental environment, the experimental data in this paper were not perfect and the data range was not large enough. The test results may fluctuate violently due to irresistible factors, which made certain flaws in the final score analysis process, and the handling of these factors was also the focus of subsequent work improvement.

Data Availability

The data that support the findings of this study can be obtained from the author upon reasonable request.

Conflicts of Interest

The author declares that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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