International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-15

https://doi.org/10.70917/ijcisim-2026-1789
Article

Application and Effect Evaluation of Blended Teaching Model of Higher Vocational Music Education in the Context of AI Era

Shifang Yang[1,*]

[1] School of Preschool Education, Chongqing Youth Vocational & Technical College, Chongqing, 400700, China
* Correspondence author: 13677645698@163.com

Abstract: In the music education industry, the use of artificial intelligence technology has greatly enriched education and teaching, education and training, music APP, intelligent systems and other aspects, injecting fresh blood into teaching activities. Based on this background, the study proposes a hybrid teaching model for English education by combining online and offline learning modes. Aiming at the deficiencies of collaborative filtering algorithm and neurocognitive diagnosis, a PMF-C&RM learning resource recommendation method integrating cognitive diagnosis and collaborative filtering is proposed, and relevant experiments are set up for verification. Taking 80 people in the English major 2024 music education as research subjects, divided into experimental and control classes, the teaching practice method was used to teach the course in four stages. The research results show that the PMF-C&RM method achieves the optimal value compared with other models, with the highest F1 value of 0.928 for simple questions and 0.932 for difficult questions, which effectively improves the effect of learning resources recommendation. Analyzing the teaching effectiveness of hybrid teaching based on PMF-C&RM in music courses, the teaching model proposed in this paper is significant in improving students' comprehensive performance ability in music.

Keywords: collaborative filtering; cognitive diagnosis; learning resource recommendation; blended teaching; music education

1. Introduction

In the rapid development of artificial intelligence (AI), higher vocational music education is also constantly exploring new teaching modes and teaching methods to better meet the needs of students. Blended teaching mode is one of the novel teaching modes, which integrates traditional face-to-face teaching and modern network teaching, providing students with more flexible and convenient learning methods [1-2]. In the context of AI, blended teaching mode has a broader space and more important role.

First of all, the blended teaching mode can be personalized according to the needs of individual students.AI technology can provide personalized learning resources and learning plans according to students' learning characteristics and weaknesses by analyzing the data of students' learning behaviors and learning habits [3-4]. This kind of personalized teaching can better meet the learning needs of different student groups and improve students' interest and initiative in learning music [5-6]. For personalized instruction in blended learning models, literature [7] examines the efficacy of AI-driven platforms to support personalized instruction in blended learning environments through a qualitative case study, analyzes teacher and student experiences and pedagogical changes, and points out that AI can parse the learning model and customize pathways, while emphasizing its integration challenges and equity implications in diverse educational scenarios. Literature [8] constructed a hybrid teaching model based on the teaching factory framework, pointed out through case validation that remote guidance can drive students to complete manufacturing and maintenance tasks, and emphasized that continuous support and cybersecurity are key elements to ensure the effective operation of personalized practice teaching. Literature [9] proposes a personalized learning framework that integrates 3D sensors and machine learning classifiers, optimizes video transmission to reduce latency and packet loss through a dual-controller mechanism, and analyzes that it is able to cluster learners according to engagement and outperforms traditional methods in terms of throughput and cost efficiency. Literature [10] analyzes three technology models and practices to support personalized learning in blended learning models through a literature review, pointing out the lack of data-driven research and implementation barriers, and emphasizing that emerging platforms offer key opportunities for learner-centered transformation of higher education. Literature [11] constructs a personalized learning intervention that integrates e-books and recommender systems in a blended learning model, analyzes it through quasi-experimental analysis to show that it improves academic performance and engagement, and emphasizes the critical pedagogical value of actionable feedback for remedial support for students with low self-regulation. Literature [12] analyzes the paths and challenges of AI-enabled personalized learning in a blended learning model, points out that intelligent tutoring and adaptive systems enable accurate feedback and customized assessment, and emphasizes that building a transparent collaborative framework is essential to dissolve ethical biases and maintain the human touch in education. Literature [13] constructed an Excel skill development framework based on four resource literacy models in a blended teaching mode, and through analyzing the feedback data of video independent learning and formula record assessment, it was pointed out that personalized dialogues and precise interventions can significantly improve the effectiveness of knowledge construction for students with large class sizes. Literature [14] constructed a personalized learning path under the blended teaching model based on the ADDIE model, and designed differentiated course routes and tracked student interactions through the Symbaloo tool, emphasizing its supportive role in adapting learning preferences and optimizing assessment design.

Second, the blended teaching mode can provide diversified learning resources and learning modes. Traditional face-to-face teaching is limited by time and space, and students can only learn through the teaching materials and lectures provided by teachers. In contrast, the blended teaching mode can provide students with more diverse music learning resources, such as online courseware, video teaching, virtual experiments, etc., by combining the online teaching platform and AI technology [15-16]. In this regard, literature [17] analyzed the development strategy and application effect of digital resources in universities under the blended teaching mode, pointed out that multimodal resources can integrate the advantages of lecture and autonomy to improve the quality of teaching, and emphasized that continuous updating of the concepts and tools is the key to guaranteeing students' comprehensive cognition and sustainable learning. Literature [18] classified the design method into three types of low, medium and high impact modes by sorting out the multiple definitions of blended learning, analyzed the applicable scenarios and implementation challenges of each mode, and emphasized that teachers should choose the best path to optimize the provision of learning resources based on the teaching basis and resource integration goals. Literature [19] analyzes the integration path of learning resources in blended teaching mode by taking the Moodle platform and the workplace world course as examples, points out that flexible platforms and open educational resources can optimize the combination of traditional and distance technologies, and emphasizes that the appropriate combination is the key to improve teaching effectiveness. Literature [20] analyzes the mechanism and effect of using catechism as OER in blended teaching mode through preliminary exploration, pointing out that although it can improve the accessibility of teaching content, it faces challenges such as low completion rate, and emphasizes the key reference value of learner experience to optimize the resource integration strategy. Literature [21] analyzes the integration path of OER in blended learning through the Linked Data approach, points out that they can break the traditional value chain to enrich the classroom environment and promote personalized learning, and emphasizes the decisive role of reuse and adaptation of OER in improving the economy and creativity of education. Literature [22] reveals the suitable conditions for the application of digital learning resources in blended teaching through systematic analysis and experiments, points out that the combination of digital and traditional resources in a ratio of 73 can optimize the structure of teacher-student interactions, and emphasizes that treating digital resources as the basic elements of the teaching and learning process instead of auxiliary tools is the key to improving the quality of teaching and learning. Literature [23] through the flipped classroom empirical analysis of blended teaching under the promotion of open digital resources on psychology course learning, pointed out that e-resources can improve academic performance and independent learning convenience, and stressed that students generally recognize its modernity but the performance advantage still needs to be further tested and demonstrated in subsequent experiments.

In addition, the blended teaching mode can also enhance students' learning participation and interactivity. In traditional higher vocational music teaching, teachers often play the role of knowledge transmitter, and students only play the role of passive acceptance. In the blended teaching mode, however, students can participate in course design and teaching activities through AI technology, and students can discuss and communicate with teachers and classmates through the social functions on the learning platform to cultivate academic communication and teamwork skills [24-25]. As for the role of blended teaching mode in enhancing students' learning engagement and interactivity, literature [26] constructed a teaching method integrating interactive modules and mini-videos based on the blended teaching mode of flipped classroom, analyzed the effect of its enhancement of learning engagement through the integration of pre-course pre-testing and classroom guided practice, and emphasized that the constructivist-oriented resource design can effectively drive the average score of learning outcome from 3.9 to 4.4. Literature [27] analyzed the effects of flipped classroom and online interaction on student engagement and learning outcomes based on a blended learning model applied to a business course on the LMS platform, comparing the test group with the control group, noting that forum engagement and quiz performance were significantly enhanced, and emphasizing that technology-enabled sense of autonomy and control effectively drove motivation and achievement of course objectives. Literature [28] analyzed the positive impact of online and offline integration on student engagement in a blended learning model through a literature review, pointing out that flexible and personalized environments can promote autonomous collaboration and positive interaction to enhance academic performance, and emphasizing the key value of digital technology-driven strategies in building an inclusive learning ecosystem. Literature [29] analyzed the effect of blended learning on learning engagement in Malaysian higher education institutions through qualitative interviews and observations, pointed out that LMS, video and project-based learning can promote online and offline positive interactions, and emphasized that technological accessibility and teacher training are the keys to guaranteeing equitable participation and educational quality. Literature [30] analyzed the current situation of student engagement in blended learning in Sri Lankan universities through a survey, noting that students showed significant engagement but were pessimistic about a fully online transition, and emphasized that optimizing the online-offline interface is key to enhancing the interactive experience and academic potential. Literature [31] analyzed the effectiveness of blended learning in an undergraduate neuropharmacology module through focus group interviews, noting that students recognized its structured design and preferred the tutorial-supported convergence model, and emphasized the synergistic value of high-quality online resources and face-to-face collaboration to enhance learning engagement. Literature [32] examined the mechanisms by which perceptions of the effectiveness of blended learning drive learning outcomes through correlation analysis, noting that student engagement plays a fully mediating role while motivation plays a moderating effect, and emphasizing that enhancing the interactive experience significantly enhances academic outputs and course attractiveness.

In this paper, we first propose online-offline blended teaching for higher vocational music education based on AI technology, then introduce the overall framework of the music learning resource recommendation method (PMF-C&RM) that integrates cognitive diagnostic model and collaborative filtering, and then recommend the corresponding test questions to the students based on the probability of the students' correct answers predicted by the model as well as the set difficulty range. Comparison experiments are conducted between PMF-C&RM method and other recommendation methods. Finally, 80 music majors from a university were selected and divided into experimental and control classes to design a three-stage music fundamentals objective as well as an example validation.

2. AI-based Blended Teaching Model for Higher Vocational Music Education

(1) Teaching goal setting

When constructing the blended teaching mode of college music courses based on AI, clear and scientific teaching goal setting is the key. First of all, the dual cultivation goals of knowledge and ability should be clarified, i.e. not only to help students master music theory knowledge, but also to cultivate their practical performance skills and innovative thinking. Specifically, the objectives of the course should include improving students' music analysis ability, performance skills as well as music creation and arranging ability.

(2) Teaching content design

The blended teaching content design of music courses in colleges and universities should fully consider the diversified needs of students and the comprehensive characteristics of the courses. First of all, in the selection of teaching content, it is necessary to take into account music theory, history, technology and creation and other fields to ensure that students have a broad vision and a solid foundation in the knowledge system. For example, music theory can be taught through interactive lectures, exercises and audio analysis provided by the online platform, so that students can independently master the basic concepts and skills of music.

(3) Selection of Teaching Methods

In music education, emphasis should be placed on cultivating students' practical ability and creativity. Therefore, the teaching design should make full use of the combination of online and offline methods to enhance students' comprehensive music literacy. Firstly, traditional classroom teaching methods are combined with modern technical means to enhance students' understanding of musical works through video teaching, case studies and interactive discussions. Secondly, practical teaching is the core of music education. Teachers should design a combination of online and offline performance and creation tasks, and encourage students to create and perform independently and cooperatively through virtual instruments, DAWs and other tools, so as to promote students to realize skill enhancement in actual operation.

(4) Integration of teaching resources

Under the blended teaching mode, the integration of teaching resources should make full use of the advantages of modern information technology and traditional music teaching to build a diversified and interactive learning environment. Traditional musical instruments, sheet music and classroom teaching resources are still the basis of teaching, but on this basis, teachers should integrate modern technological tools such as online learning platforms, virtual musical instruments and DAWs to provide students with a more flexible learning experience.

3. Personalized Recommendation of Online Music Teaching Resources for Higher Vocational Education

3.1. Recommendation algorithms

3.1.1. Recommendation algorithms based on collaborative filtering

User-based collaborative filtering algorithm recommendation strategy is based on the collected historical behavioral information data of the relevant users to calculate the similarity between the user and the user, through the degree of similarity to find similar to the target user behavioral information or preferences and habits of the individual, based on user-based collaborative filtering recommendation algorithm process is shown in Figure 1.

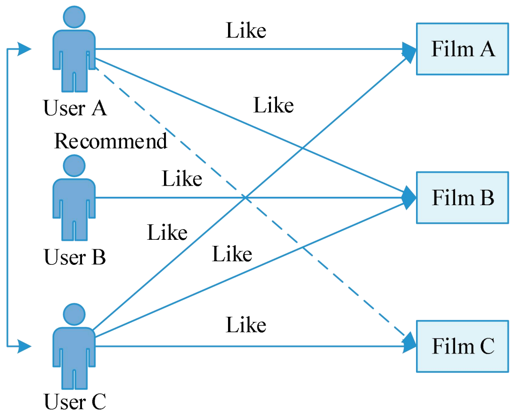

Figure 1. Collaborative filtering recommendation

3.1.2. Content-based recommendation algorithms

Content-based recommendation algorithms have been used earlier in various fields and the required recommendation data for them are easier to obtain. The data is mined and analyzed by collecting the user's behavioral information data, and the result of data mining is to get the relevant vectors with representational properties. Then the similarity measure between the resources to be recommended and the vectors is calculated, and finally the recommendation is made to the user according to the value of the similarity. The steps involved in recommendation: data acquisition, data cleaning, data organization mining and algorithm design.

3.1.3. Probability matrix decomposition

Matrix factorization (MF) methods are also commonly used in various recommender systems, and

MF realizes the association between users and items based on the personality trait information contained in the scoring matrix. Similarly matrix factorization is used in test question resource recommendation by analyzing the learner-test question score matrix, predicting the score of the test question to be recommended, and finally recommending the test question based on the score.

The original high-dimensional matrix can be obtained by inner product operation of the low-dimensional matrix obtained after matrix decomposition. For example, in test recommendation, the student-test-question rating matrix is $R \in R^{N \times M}$, the number of students is N, and the number of test questions is M. The matrix decomposition model decomposes this rating matrix into the student's eigenmatrix $S \in R^{N \times f}$ and the test question's eigenmatrix $E \in R^{f \times M}$ by decomposing it into the student's eigenmatrix $S \in R^{f \times M}$, which is $R \approx S^T E$. The feature vector of student i is represented by the i th column of S, $E_i \in R^f$, the feature vector of test question j is represented by the j th column of E, $E_j \in R^f$, and the predicted scores are represented by the inner product of the test question's feature vectors and the student's feature vectors, which can be described as Eq. (1):

$$\hat{R}_{ij} = p\left(S_i, E_j\right) \tag{1}$$

3.2. Cognitive Diagnostic Theory

3.2.1. Project Response Theory

The items contain three parameters: the differentiation parameter a, that is, the slope of the curve on the slope of the curve, indicating the different students in the various test questions on the level of differentiation; the difficulty parameter b, that is, the curve can force the position on the ruler, indicating the difficulty of the test questions; the parameter c guessing the probability of the right answer, that is, the asymptote.

Commonly used item characteristic function models are single-parameter model, two-parameter model and three-parameter model. The item characteristic function of each model is shown in equations (2), (3) and (4):

Single-parameter model:

$$P_{ij}(\theta_j) = \frac{1}{1 + e^{-V(\theta_j - b)}} \tag{2}$$

A two-parameter model:

$$P_{ij}(\theta_j) = \frac{1}{1 + e^{-Va_j(\theta_j - b_j)}} \tag{3}$$

Three-parameter modeling:

$$P_{ij}(\theta_j) = c_j + (1 - c_j)\frac{1}{1 + e^{-Va_j(\theta_j - b_j)}} \tag{4}$$

$P_{ij}(\theta_i)$ denotes the specific meaning of the probability of a student answering the music test question j correctly when the musical ability level is θ_i, where V is the constant 1.7, e is the base of the natural logarithm which is $\ln N$, i is the numbering of the student, θ_i stands for the value of the student's musical ability of i, j is the numbering of the test questions, and a_j, b_j, and c_j denote the differentiation, difficulty, and guessing parameters of test question j, respectively.

3.2.2. DINA model

The DINA model (Deterministic Inputs, Noisy "And"-gate model) is a multidimensional discrete cognitive diagnostic model for item response functions defined as in Eq. (5), which represents the probability of a student's i answering correctly on a music test question j:

$$P\left(x_{ij} = 1 \middle| \alpha_i, q_j, n_{ij}\right) = \left(1 - s_j\right)^{n_{ij}} g_j^{(1 - n_{ij})} \tag{5}$$

n_{ij} denotes that student i completes the answer to test question j without taking into account the error rate and guessing rate, and the number of knowledge points is K, and the calculation is expressed as formula (6):

$$n_{ij} = \prod_{k=1}^{K} \alpha_{ik}^{q_{jk}} \tag{6}$$

For student i, the value of n_{ij} may be 1 only if he/she has mastered the relevant music knowledge attribute of test question j. When n_{ij} takes the value of 0, it means that student i has not mastered any of the relevant knowledge attributes of music j. There are only two parameters for each item in the DINA model, i.e., the s failure parameter and the g guessing parameter.

$$s_j = P\left(x_{ij} = 0 \middle| \alpha_i, q_j, \eta_{ij} = 1\right) \tag{7}$$

$$g_j = P\left(x_{ij} = 1 \middle| \alpha_i, q_j, \eta_{ij} = 0\right) \tag{8}$$

The association between music level and music knowledge points is portrayed in the DINA model by introducing the test knowledge point association matrix Q.

3.2.3. Neurocognitive diagnostic models

In traditional cognitive diagnostic models, the interaction function between students and test items mainly relies on expert design, and the disadvantages of manual design are that it is more labor-intensive and the simplified function fails to reflect the intricate relationship between subjects and test items. However, using the combination of neural networks and cognitive diagnostic-related techniques provides a new idea, and the neurocognitive diagnostic model solves this problem on the basis of traditional cognitive diagnostic models, which learns the interaction functions of students, knowledge points and test scores directly from the data instead of designing them manually, and has a good performance on the assessment of students' knowledge status and ability level.

The following constraints are made to ensure that each dimension corresponds to the level of mastery of the corresponding student on the corresponding knowledge point at the end of the model training.

(1) The input layer needs to contain $F^s \circ F^{kn}$ (“ $\circ$ ” means multiply by element), which is done so that each dimension in F^s corresponds to a knowledge point in the corresponding dimension in F^{kn}.

(2) The “monotonicity assumption” constraint. The probability that a student will answer a music question correctly increases monotonically and not necessarily strictly monotonically if the student's mastery of the knowledge point is increasing. In the training process of the model, F^{kn} controls the dimensions of F^s that need to be adjusted, and when the predicted value of the test answer is smaller than the true answer value, the value of F^s will be increased, and vice versa, the value of F^s will be decreased.

3.3. Music Resource Recommendation Based on Cognitive Diagnosis and Collaborative Filtering

3.3.1. PMF-C&RM Methodological Framework

PMF-C&RM is a music learning resource recommendation method that fuses the cognitive response model C&RM and the probability matrix decomposition method PMF in collaborative filtering. Figure 2 shows the overall framework of fusing cognitive diagnostic model and collaborative filtering recommendation method, from which it can be seen that the input data are the learner's response result matrix and music knowledge point association matrix. First, the cognitive diagnostic model obtains parameters such as the learner's music learning ability, knowledge point mastery level, and multidimensional features of learning resources through learning the input data, which in turn can predict the learner's potential responses on music knowledge points. Then, the probability matrix decomposition method, based on the combination of a priori information and existing music feature data, also predicts the learners' responses on music test questions. Finally, the two predictions are combined according to the adjustment ratio parameter, and the task of recommending music learning resources is completed according to the difficulty range set by the learners. The above parameter ρ is the moderating ratio parameter of the individual characteristics of the target learners represented by the cognitive diagnosis method and the common characteristics among the learners represented by the probability matrix decomposition method in the prediction of the answer results.

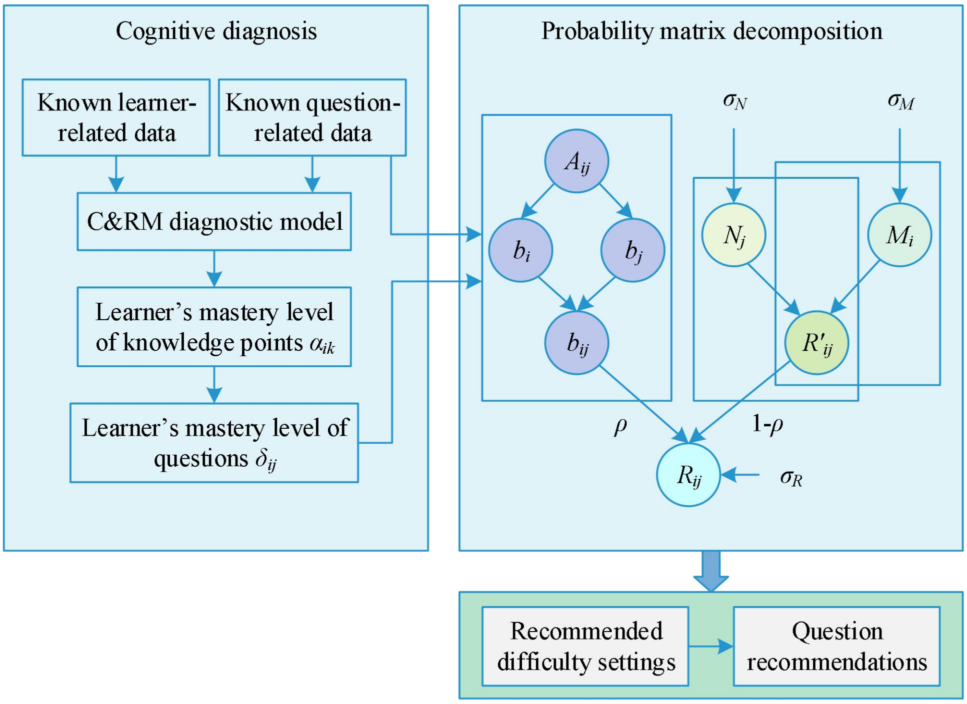

Figure 2. The overall framework of the PMF-C&RM method

3.3.2. PMF-C&RM methodology modeling

(1) C&RM model evaluation

In the cognitive diagnosis part, the input data of the C&RM model are learner-related data and test question-related data, in which the learner-related data contain the learner's response result matrix and the effort factor, which is mainly measured by the learner's learning activity data, and the test question-related data are mainly the correlation relationship between the test questions and the knowledge points. Through the C&RM model, we can get the mastery level of learning on each music knowledge point, as well as the dependency matrix of test questions on knowledge points, and the answer prediction matrix of the learners excluding the error and guessing factors:

$$R'_{ij} = \delta_{ij} \tag{9}$$

In Eq. (9), δ_{ij} denotes the learner's i mastery of test question j.

(2) Combining test question answering prediction with PMF

After the diagnostic evaluation of the C&RM model, the learner's a priori score b_i and the a priori score of the test question b_j are extracted from the learner answer prediction matrix R' as the a priori information of the PMF, and the extraction formula is:

$$b_i = \frac{1}{V} \times \sum_{j=1}^{V} R'_{ij} \tag{10}$$

$$b_j = \frac{1}{U} \times \sum_{i=1}^{U} R'_{ij} \tag{11}$$

In Eq. (10), b_i denotes the a priori score of learner i, computed from the i th row of matrix R', presenting the degree of difference between learners. In Eq. (11), b_j denotes the a priori score of trial j, computed from the j th column of the matrix R', presenting the degree of variation between trials.

After introducing the a priori scores b_i and b_j of learners and music learning resources, the prediction scores of the personalized learning resource recommendation method PMF-C&RM can be obtained by combining the learner feature matrix M_i and trial question feature matrix N_j obtained by the probability matrix decomposition method:

$$\eta_{ij} = \rho(b_i + b_j) + (1-\rho)M_i^T N_j \tag{12}$$

In Eq. (12), η_{ij} is the predicted score of learner i on music test question j, ρ is a moderating scale parameter, and $\rho \in [0,1]$. When the value of ρ is larger, the influence of learner's personality traits on the predicted answer results is also larger. In particular, when $\rho = 1$, the above learning resource recommendation method relies entirely on the recommendation method based on the cognitive diagnostic model, and when $\rho = 0$, the test question recommendation method relies entirely on the recommendation method of probability matrix decomposition.

3.3.3. Recommendations for test questions that incorporate preset levels of difficulty

The PMF-C&RM test question recommendation method is not a simple recommendation based on the learner's interest in learning and the difficulty of the test questions, but rather a combination of the target learner's personality characteristics, the common characteristics among similar learners, and the test question characteristics. The difficulty of the recommended test questions is set by the learner according to his/her own situation, assuming that the set difficulty range is $[\beta_1, \beta_2]$, $\beta_1 < \beta_2$, where β_1 denotes the lower bound of the probability that the learner will correctly play the music test questions, and β_2 is the upper bound of the probability that the learner will correctly answer the test questions, then the PMF- C&RM recommendation method will recommend to the learner the set of test questions E_{rec} whose probability of answering the test questions is within the range of the preset parameters from the set of test questions E_{dif} to be recommended according to the learner's predicted answering, and the mathematical expression is shown below:

$$E_{rec} = \left\{ E_j \left| E_j \in E_{res}, D_{ij} \in \left[\beta_1, \beta_2\right] \right.\right\} \tag{13}$$

$$D_{ij} = P\left(r_{ij} = 1 \left| \Omega_j, \theta_i, \eta_i \right.\right) \tag{14}$$

In Eq. (13), E_{res} denotes the set of test questions to be recommended in the test bank, E_{rec} denotes the set consisting of test questions E_j in E_{res} that satisfy the recommendation conditions, and the value of D_{ij} shown in Eq. (14) denotes the probability that a learner i will correctly answer the test question j under the conditions of considering the characteristics of the learner and the characteristics of the test questions.

3.4. Experimental validation

3.4.1. Introduction to data sets

The data used in the experiment is the FrcSub dataset, which is a real public dataset on the addition and subtraction rules for elementary school fractions and contains 20 test questions, each of which involves 8 knowledge points. It also provides records of 536 students' scores on these test questions. In addition, the FrcSub dataset contains only objective questions, and students' responses to the test questions are only available in the form of right and wrong answers, which are denoted by 0 and 1, respectively.

3.4.2. Chi-square test for score prediction component

The validity of the PMF-C&RM method in the part of students' score prediction was verified statistically, i.e., the chi-square test was used to show whether the students' predicted scores and the students' real scores were correlated. In this paper, 30% of the students' response records on 60% of the test questions were randomly selected as the basis for the chi-square test, and the specific statistical results are shown in Table 1. Among them, r_{nm}=1 indicates that the students actually answered the test questions correctly, r_{nm}=0 indicates that the students actually answered the test questions incorrectly, $y_{nm} = r_{nm}$ indicates that the predicted results of the students' answers are the same as the real results of answering the questions, $y_{nm} \neq r_{nm}$ indicates that the predicted student response results are inconsistent with the true response results.

Based on the randomly selected answer records of the dataset, it is calculated that $x^2 = 875.572$ with a confidence level of 0.005, and based on the chi-square test table, it is calculated that $\rho < 0.005$. Therefore, according to the chi-square test it can be verified that there is a correlation between the students' predicted scores obtained by the PMF-C&RM personalized learning resource recommendation algorithm and the students' real scores, i.e., it proves the validity of the PMF-C&RM model in the prediction of students' scores part.

Table 1. Chi-square test results

Divide into groups	$y_{nm} = r_{nm}$	$y_{nm} \neq r_{nm}$	**Amount to**
r_{nm} =1	1045	98	1143
r_{nm} =0	219	605	824
Amount to	1264	703	1967

3.4.3. Recommended Comparison Experiments

(1) Experimental evaluation metrics

In order to evaluate the recommendation effect of MNCD-NMF model and other comparative models on simple and difficult questions, this paper takes precision rate, recall rate and F1 value as the evaluation indexes. The formulae for each index are shown in Eq. (15), Eq. (16) and Eq. (17):

$$\Pr ecision = \frac{TP}{TP + FP} \tag{15}$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{16}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{17}$$

(2) Comparison of experimental results

In this paper, a random selection method was used to select 70% of the students in the dataset as the training set and the remaining 30% as the test set. After that, for each student in the test set, 40%, 50% and 60% of the test questions were selected sequentially as the test set (to be recommended as the test set), and the remaining test questions were used as the training set.

In this paper, comparative experiments were conducted using the PMF-CD model, the NMF model, and the PMF-C&RM model, respectively, in which PMF-CD is a personalized test-question recommendation method that combines the probabilistic matrix decomposition model (PMF) and the DINA cognitive diagnostic model. The recommendation effects of different recommendation methods on simple and difficult test questions were evaluated by the above three experimental indexes, and the results of the test question recommendation comparison experiments are shown in Table 2.PMF-C&RM performs optimally, and PMF-C&RM achieves the optimal value in most cases in the various indexes of simple and difficult questions, for example, the F1 value of the simple questions is up to 0.928, and the F1 value of the difficult questions is up to 0.932.

Table 2. Recommended solutions for easy and difficult questions

		Simple questions			**Difficult questions**		
		Test set proportion			**Test set proportion**		
	Model	40%	50%	60%	40%	50%	60%
Precision	PMF-CD	0.891	0.882	0.916	0.905	0.915	0.937
	NMF	0.896	0.854	0.879	0.891	0.926	0.931
	PMF-C&RM	0.904	0.885	0.912	0.909	0.919	0.939
Recall	PMF-CD	0.782	0.778	0.795	0.871	0.818	0.822
	NMF	0.944	0.908	0.922	0.831	0.902	0.916
	PMF-C&RM	0.953	0.934	0.943	0.907	0.939	0.922
F1	PMF-CD	0.833	0.827	0.851	0.887	0.864	0.876
	NMF	0.919	0.881	0.903	0.860	0.914	0.923
	PMF-C&RM	0.928	0.908	0.927	0.909	0.929	0.932

3.4.4. Difficulty range parameter experiments

In order to verify whether the test questions recommended by the PMF-C&RM model meet the requirements of the recommended difficulty, this experiment randomly selected 30% of the students' response records on 60% of the test questions as the test set. And the test question difficulty range is divided into 10 intervals, the recommended test question difficulty parameter β is from 0 to 1, and the span of each interval is 0.1, and the test questions are recommended to the students with $[\beta - 0.1, \beta + 0.1]$ in order as the test question difficulty range, and the results of the experiment are shown in Figure 3.

The correct response rate SR of students on the recommended questions increases as the difficulty parameter of the recommended questions increases. For example, when the difficulty range of the recommended questions is [0.1, 0.2], the questions recommended to the students are relatively difficult, and in the recommended question list, the correct response rate SR of the students is only 0.15; when the difficulty range of the recommended questions is [0.7, 0.8], the recommended questions are relatively easy, and in the recommended question list, the correct response rate SR of the students increases to 0.85. Therefore, the experiment shows that the PMF-C&RM model can recommend appropriate difficulty learning resources to students.

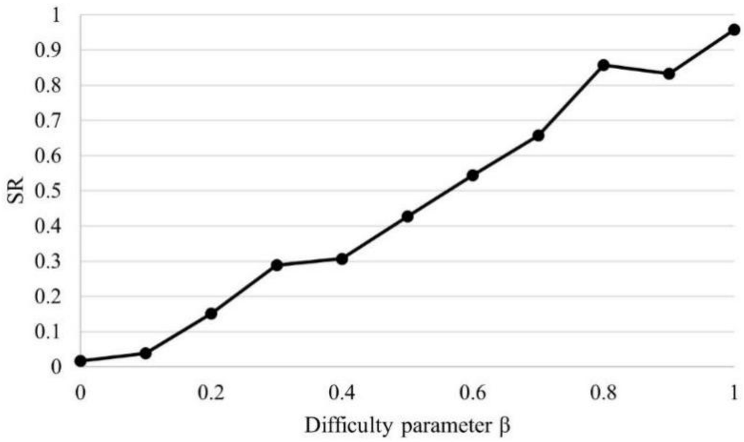

Figure 3. The impact of parameter β value on the SR index

3.4.5. Recommended case studies

The main purpose of personalized test question recommendation is to provide students with personalized and targeted learning resources to help them better master their knowledge and improve their learning efficiency. In this section, 30% of the students' answer records on 60% of the test questions are randomly selected as the test set, and then one student C is randomly selected from the test set students to analyze the PMF-C&RM model's test question recommendation for this student. First, the students' knowledge point mastery was accurately analyzed by the multifactor neurocognitive diagnostic model, and Student C's mastery of the eight knowledge points in the FrcSub dataset is shown in Figure 4. From the figure, it can be seen that Student C's mastery of knowledge points S1, S4, S6, and S7 is weak, and the mastery level of knowledge points S2 and S8 is 0.87 and 0.83, which is better.

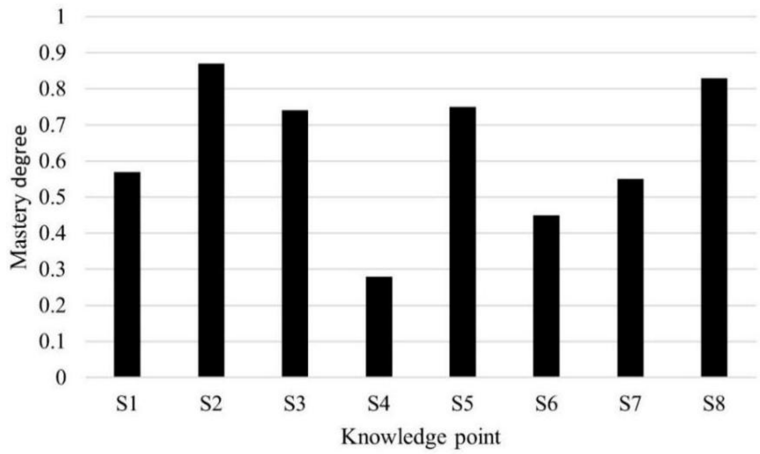

Figure 4. Student C's mastery level of key knowledge points

After that, the probability of correctly answering the test questions in the test set is obtained from Student C according to the PMF-C&RM model, and the test questions in the test set (the set of test questions to be recommended) are recommended to the students by setting the difficulty range parameter of the model. The predicted responses of Student C are shown in Table 3, where Test Questions 2, 6, 8, 10, 12, 13, 16, and 20 are the training set test questions that Student C has responded to, and the other test questions are the test set test questions that Student C has not responded to.

When selected for recommendation in the range of difficulty in the interval [0.4,0.5], Student C's predicted probability of correctly answering test questions for Test Question 1, Test Question 5, Test Question 7, and Test Question 18 are in the range of 0.4 to 0.5, and therefore the above four test set questions will be recommended to Student C. According to the knowledge point association Q matrix, it can be found that these four questions include the knowledge points S1, S4, S6 and S7, which are not mastered by Student C. This in turn verifies the reasonableness of the recommendation results.

Table 3. Student C's predicted response performance

Examination questions	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Predicted score	0.447	/	0.073	0.963	0.497	/	0.487	/	0.725	/
Examination questions	11	12	13	14	15	16	17	18	19	20
Predicted score	0.963	/	/	0.943	0.782	/	0.947	0.452	0.647	/

4. Evaluation of blended teaching effect in higher vocational music education

4.1. Study design

(1) Subjects of the study

This study selected two parallel classes in the direction of music education of music major 2024 in an applied undergraduate university, in which the number of experimental class A is 39 and the number of control class B is 41. The students were divided into classes according to the principle of balanced art scores in the college entrance examination, and there was no significant difference between the two classes ($t=0.188$, $df=74.903$, $p=0.849>0.05$), and the two classes had a similar level of music as a whole.

(2) Research program

This study was conducted based on the spring semester vocal music course of the 2024-2025 academic year. At the beginning of the semester, the two classes took a pre-study test on the music course as Chopin's Fantasy Polish Dances. It was divided into five aspects of pitch, rhythm and strength, timbre and pattern, with a full score of 10 points, divided into five grades: 9-10 points, 7-8 points, 5-6 points, 3-4 points, and 1-2 points. The three teachers of the course team graded the students' assignments according to the above five aspects, and each item was set to 20 points for a total of 100 points in order to facilitate the teachers' grading habits. During the experimental period, the two classes were taught in four stages of the course using PMF-C&RM based recommended hybrid and traditional teaching methods, respectively, pre-test (0) and post-test (1, 2, 3).

4.2. Data results and analysis

By calculating the mean and variance of the data of each comprehensive performance ability of pitch, rhythm, intensity, timbre and composition in the pre-test and post-test of the experimental group, the results were obtained as shown in Table 4. It can be found that the means of all test elements in the post-test are higher than those in the pre-test, indicating that there is an improvement in the students' comprehensive performance ability in basic music knowledge. Comparing the variance of the pre and post-tests, the strength, and tune elements of the post-test are reduced compared to the pre-test, which shows that students' learning of strength and tune elements is characterized by the reduction of individual differences.

Table 4. Pre-and post-test results of the experimental group

		Pitch	Rhythm	Intensity	Tone	Musical form	Total points
	Figure	12	12	12	12	12	12
Pre-test	Average value	7.0021	5.8325	5.6147	3.2915	4.5962	26.0318
	Variance	3.584	2.497	1.913	1.717	8.294	19.021
	Figure	12	12	12	12	12	12
Post-test	Average value	10.7123	10.5702	10.2543	6.5302	8.7803	47.6241
	Variance	2.714	2.003	0.714	0.822	1.682	11.825

Figure 5 shows the comparison of the mean values of the performance abilities of the elements of the pre-test and the post-tests of different stages and the mean values of the performance abilities of the elements of the pre-test and the post-tests of the three stages. The figure shows a gradual increase in the data of the experimental group of students in the three stages of learning post-test.

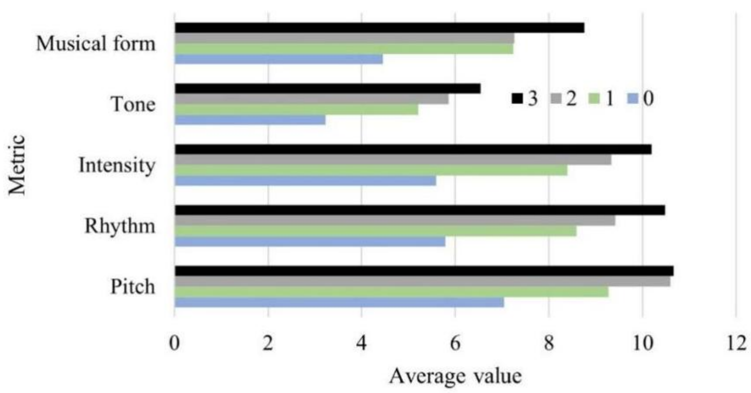

Figure 5. Summary of performance metrics for each element in the experimental group

By calculating the mean and variance of the data of each comprehensive performance ability of pitch, rhythm, intensity, timbre and composition in the pre-test and the third post-test of the control group, the results were obtained as shown in Table 5. It can be found that the means of all test elements in the third post-test are higher than those in the pre-test, indicating that there is an improvement in the students' comprehensive performance ability in basic music knowledge. Comparing the variance of the pre and post-tests, the pitch and rhythm elements of the post-test are reduced compared to the pre-test, showing that students are characterized by reduced individual differences in the learning of pitch and rhythm elements.

Table 5. Pre-and post-test results in the control group

		Pitch	Rhythm	Intensity	Tone	Musical form	Total points
	Figure	12	12	12	12	12	12
Pre-test	Average value	6.8543	7.7321	5.5242	3.1873	4.4472	25.0931
	Variance	2.781	2.275	3.064	1.135	6.654	42.821
	Figure	12	12	12	12	12	12
Post-test	Average value	9.1153	8.1402	8.0921	4.4216	5.5324	33.5426
	Variance	0.867	1.547	1.132	0.525	7.709	19.129

Figure 6 shows a comparison of the means of the performance abilities for each element of the pre-test and the three post-tests and the means of the performance abilities for each element of the pre-test and the third post-test. The data for the control group of students on the three post-tests showed a steady up and down movement over the three phases of study.

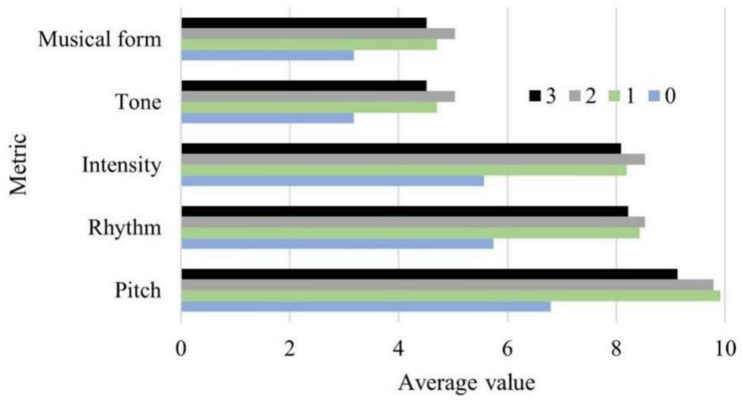

Figure 6. Summary of performance metrics for control group elements

By comparing the pre- and post-test data of the experimental group and the control group, it can be concluded that after the recommended teaching method based on PMF-C&RM students' comprehensive performance ability in music has been improved, especially the students' compositions have been improved significantly compared to other abilities. From the above test results show that students' performance ability of music basics before and after the blended teaching is significantly improved, and from the interview, the author further understands the students' feelings during the learning process, "I like this kind of music class, I don't have to sing all the time"; "I enjoy composing, I 'always do it' and I would love to keep learning more"; "I like conducting the (tunes) I compose, my teacher didn't teach us at school and I still want to learn"; "I want (to) go to concerts, I want to hear the tones of a lot of instruments." Through the students' feedback on the class, the author believes that the students are not only interested in the basic knowledge of music learned in the class, but also have a great desire to learn music in the future. Through the students' descriptions, it can be found that in the PMF-C&RM recommended blended teaching classroom, the students' understanding of musical works is not only limited to "good" and "bad", but also able to explore and capture the elements of music, and express themselves freely in their compositions. They are able to explore and capture the elements of music and express themselves freely in their compositions. In listening and appreciation, students naturally develop their own aesthetic orientation.

5. Conclusion

The study proposes a blended teaching model of higher vocational music education by integrating cognitive response modeling and collaborative filtering algorithm for learning resource recommendation method (PMF-C&RM) in the context of AI. The PMF-C&RM method is applied to recommendation experiments, and the experimental part is investigated by using chi-square test, comparative experiments, and setting different difficulty parameter ranges. Meanwhile, the teaching effect evaluation part was conducted by selecting experimental subjects and dividing them into experimental and control classes for data analysis. The results show that the PMF-C&RM model with the highest F1 value of 0.928 for simple questions and the highest F1 value of 0.932 for difficult questions is capable of recommending learning resources recommendations of appropriate difficulty for students. Based on PMF-C&RM recommended teaching and traditional teaching in the teaching process has a significant impact on students' cognitive ability of basic music knowledge, to achieve accurate and personalized learning resources pushing, and to provide technical support for the reform of higher vocational music education.

About the Author
Shifang Yang, female, born in November 1984, postgraduate, lecturer. She graduated from the School of Music, Southwest University, majoring in Musicology. She is currently working at Chongqing Youth Vocational & Technical College, with her main research interests in vocal music performance and teaching research. She mainly teaches courses including Basic Vocal Music, Music Theory, and Solfège & Ear Training.

References

1. Hou, J., & Xue, J. (2023). Impact of the blended teaching model on learning outcomes. International Journal of Emerging Technologies in Learning (Online), 18(5), 192.
2. Wang, X. H., Wang, J. P., Wen, F. J., Wang, J., & Tao, J. Q. (2016). Exploration and Practice of Blended Teaching Model Based Flipped Classroom and SPOC in Higher University. Journal of Education and Practice, 7(10), 99-104.
3. Musayeva, S. (2025). Effective Strategies for Teaching Music Online or in Blended Classrooms. Porta Universorum, 1(9), 5-15.
4. Hashim, S., Omar, M. K., Ab Jalil, H., & Sharef, N. M. (2022). Trends on technologies and artificial intelligence in education for personalized learning: systematic literature. Journal of Academic Research in Progressive Education and Development, 12(1), 884-903.
5. Rahman, Q. (2024). Significance role of artificial intelligence technology to optimize blended teaching in higher education. Journal of Education and Development, 16(27), 1.
6. Zohuri, B., & Mossavar-Rahmani, F. (2024). Revolutionizing education: The dynamic synergy of personalized learning and artificial intelligence. International Journal of Advanced Engineering and Management Research, 9(1), 143-153.
7. Kumar, R. (2025). Personalized Learning Through AI: A Case Study Of Implementation In A Blended Learning Environment. International Journal of Scientific Research & Engineering Trends, 11(6).
8. Mourtzis, D., Panopoulos, N., & Angelopoulos, J. (2023). A hybrid teaching factory model towards personalized education 4.0. International Journal of Computer Integrated Manufacturing, 36(12), 1739-1759.
9. Khadidos, A. O., Manoharan, H., Khadidos, A. O., N. Alanazi, M., Alanazi, F., & Selvarajan, S. (2025). Personalized learning in hybrid education. Scientific Reports, 15(1), 18176.
10. Alamri, H. A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environments in higher education. TechTrends, 65(1), 62-78.
11. Yang, C. C., & Ogata, H. (2023). Personalized learning analytics intervention approach for enhancing student learning achievement and behavioral engagement in blended learning. Education and Information Technologies, 28(3), 2509-2528.
12. Ali, A., Farid, R. Z., & Kananah, A. (2025, December). AI in Blended Learning: Enhancing Personalization, Efficiency, and Accessibility. In 2025 International Conference on Computer and Applications (ICCA) (pp. 1-6). IEEE.
13. Clutterbuck, P., & Lewis, D. (2019). Personalized Blended Learning via New Media and Formative Assessment. International Journal of Learning, 5(1), 12-18.
14. Campos Ortuño, R. A., & Hernández Serrano, M. J. (2020). Design of Blended Learning Personalized Itineraries for Higher Education. In Blended Learning: Convergence between Technology and Pedagogy (pp. 183-209). Cham: Springer International Publishing.
15. Janse van Rensburg, E. D., & Oguttu, J. W. (2022). Blended teaching and learning: Exploring the concept, barriers to implementation and designing of learning resources. South African Journal of Higher Education, 36(6), 285-296.
16. Sandanayake, T. C. (2019). Promoting open educational resources-based blended learning. International Journal of Educational Technology in Higher Education, 16(1), 1-16.
17. Yang, G. (2022). A study on the application of digitized resources in English language teaching under a blended teaching model: exploration and reflection on online teaching in the context of the pandemic. Pacific International Journal, 5(1), 56-63.
18. Alammary, A., Sheard, J., & Carbone, A. (2014). Blended learning in higher education: Three different design approaches. Australasian Journal of Educational Technology, 30(4).

19. Shaykina, O. I. (2015). Blended learning in English language teaching: Open educational resources used for academic purposes in Tomsk Polytechnic University. Mediterranean Journal of Social Sciences, 6(3), S5.
20. Bandalaria, M. D. P. (2019). Massive open online courses as open educational resources in a blended teaching and learning mode of instructional delivery in higher education. International Journal of Innovation and Learning, 25(2), 156-169.
21. Piedra, N., Chicaiza, J., López, J., & Caro, E. T. (2016, April). Integrating OER in the design of educational material: Blended learning and linked-open-educational-resources-data approach. In 2016 IEEE Global Engineering Education Conference (EDUCON) (pp. 1179-1187). IEEE.
22. Vladimirovna, L. N., & Valentinovna, Z. A. (2018). Digital learning resources: Enhancing efficiency within blended higher education. Science for Education Today, 8(6), 121-137.
23. Sorokova, M. G. (2020). E-course as blended learning digital educational resource in university. Psychological science and education, 25(1), 36-50.
24. Serrano, D. R., Dea-Ayuela, M. A., Gonzalez-Burgos, E., Serrano-Gil, A., & Lalatsa, A. (2019). Technology-enhanced learning in higher education: How to enhance student engagement through blended learning. European journal of education, 54(2), 273-286.
25. ZHU, X., TANG, X., QIAN, J., & SUN, H. (2023). The impact of teacher-student interaction on learning engagement in blended learning. US-China Education Review A, 13(2), 95-100.
26. Alkhatib, O. J. (2018). An interactive and blended learning model for engineering education. Journal of Computers in Education, 5(1), 19-48.
27. Sahni, J. (2019). Does blended learning enhance student engagement? Evidence from higher education. Journal of E-learning and Higher Education, 2019(2019), 1-14.
28. Joshi, D., Zalte, S. M., Johny, K. R., & Mahajan, D. A. (2023). The impact of blended learning on student engagement in the digital era. European Chemical Bulletin, 12(1), 727-735.
29. Ahmed, N. H., Andersion, J., & Martínez, A. G. (2024). Innovative Blended Learning Approaches to Enhance Student Engagement in University. Journal of Teaching and Learning, 1(1), 1-21.
30. Gamage, K. A., Gamage, A., & Dehideniya, S. C. (2022). Online and hybrid teaching and learning: Enhance effective student engagement and experience. Education Sciences, 12(10), 651.
31. Morton, C. E., Saleh, S. N., Smith, S. F., Hemani, A., Ameen, A., Bennie, T. D., & Toro-Troconis, M. (2016). Blended learning: how can we optimise undergraduate student engagement?. BMC medical education, 16(1), 195.
32. Han, X. (2025). Associations between effectiveness of blended learning, student engagement, student learning outcomes, and student academic motivation in higher education. Education and Information Technologies, 30(8), 10535-10565.