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Environmental Literacy Education and Sustainable Development in Schools Based on Teaching Effectiveness

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ABSTRACT

As global environmental issues become increasingly severe, environmental awareness and the concept of sustainable development have gradually become international consensus. At this time, it is particularly important to explore the research on environmental literacy education and sustainable development in schools based on teaching effectiveness. In order to explore the relationship between environmental literacy education and sustainable development in schools, this study carries out related research. An evaluation index system for the teaching effectiveness of environmental literacy education is presented, and the method and process for evaluating the teaching effectiveness of environmental literacy education based on fuzzy comprehensive evaluation are described. Based on the educational relationships among knowledge points and between knowledge points in the stored knowledge graph of environmental literacy education that promotes school sustainable development, the curriculum knowledge model is designed, and the environmental literacy education knowledge model is constructed. The recommendation method based on user knowledge transfer is applied to the resource recommendation scenario of environmental literacy education that promotes school sustainable development, and the method process is provided. Experimental results verify the effectiveness of the proposed methods.

1. INTRODUCTION

As global environmental issues become increasingly severe, environmental awareness and the concept of sustainable development have gradually become international consensus [1-5]. The education sector, under this broader context, also needs to pay attention to the importance of environmental literacy education to cultivate future citizens with environmental awareness and sustainable development capabilities [6-11]. Schools are the cradle of talent cultivation, and the quality and methods of education directly affect students' lifelong development. Therefore, it is particularly important to explore the research on environmental literacy education and sustainable development in schools based on teaching effectiveness [12-15]. In the process of implementing environmental literacy education, schools can improve their sustainable development capabilities by adjusting education concepts, content, and methods. Research results help educators understand the importance of environmental literacy education, improve teaching effectiveness, and provide students with better educational resources.

Evaluating teaching effectiveness wisely has always been a technical challenge. Gong and Wang [16] addresses this issue from a big data mining perspective, using fuzzy comprehensive analysis. A data-driven teaching effectiveness intelligent evaluation framework based on fuzzy comprehensive analysis is proposed. First, timely collection of online course business data as a basis, including teacher performance, teaching content, and student feedback. Specifically, the initial data is encoded in a structured format, from which students' behavioral characteristics can be analyzed. Then, the teaching effectiveness evaluation results are calculated using fuzzy comprehensive analysis. Singh and Singh [17] mainly focuses on demonstrating the role of education in sustainable development and the challenges faced by quality education. A Sustainable Development Goals (SDG) index is provided to score the performance of states, showing their status more clearly. Khovrak et al. [18] identifies the results of the project "Strengthening Social Responsibility for Sustainable Development in Universities." Research methods include case studies, sociological surveys, and graphical methods. The research results promote ethical behavior and social responsibility in academic environments, involve students in university decision-making, promote dialogue and cooperation, and drive the development of innovation culture and the implementation of university social responsibility projects.

In the application scenario of this study, there are some shortcomings in the existing teaching effectiveness evaluation, knowledge model construction, and teaching resource recommendation methods. Existing teaching effectiveness evaluation methods often focus too much on students' test scores, ignoring the evaluation of students' practical operation ability, environmental awareness, and actual behavior. Some knowledge models may not keep up with the rapid development of the environmental and education fields, resulting in outdated or incomplete model content. Some teaching resource recommendation methods may overlook students' personalized needs, leading to recommended resources that do not meet students' actual needs. Therefore, this study conducts research on environmental literacy education and sustainable development in schools based on teaching effectiveness. Section 2 of the study presents the evaluation index system for the teaching effectiveness of environmental literacy education and describes the method and process for evaluating the teaching effectiveness of environmental literacy education based on fuzzy comprehensive evaluation. Section 3 of the study designs a curriculum knowledge model based on the educational relationships among knowledge points and between knowledge points in the stored knowledge graph of environmental literacy education that promotes school sustainable development, constructing the environmental literacy education knowledge model. Section 4 of the study applies the recommendation method based on user knowledge transfer to the resource recommendation scenario of environmental literacy education that promotes school sustainable development and provides the method process. Experimental results verify the effectiveness of the proposed methods.

2. ENVIRONMENTAL LITERACY EDUCATION TEACHING EFFECTIVENESS EVALUATION

Through teaching effectiveness evaluation, educators can understand which environmental literacy education methods are effective and which need improvement, thereby optimizing teaching methods and improving teaching quality. This helps to assess students' learning outcomes in environmental literacy education, promptly discover students' knowledge gaps and needs, and provide targeted educational resources. The evaluation index system for the teaching effectiveness of environmental literacy education should comprehensively and multi-dimensionally evaluate students' environmental knowledge, skills, attitudes, and behavior. The index system constructed in this study is as follows:

Knowledge mastery:

a) Basic environmental knowledge: Understand basic concepts, principles, and policies and regulations in the environmental field.

b) Interdisciplinary knowledge: Understand geography, biology, chemistry, and other interdisciplinary knowledge related to environmental protection.

c) Environmental problem analysis: Possess the ability to analyze environmental problems and understand the causes and impacts of environmental issues.

Skill development:

a) Environmental protection skills: Master practical environmental protection skills, such as waste sorting, energy-saving emission reduction, and ecological restoration.

b) Problem-solving ability: Possess the ability to analyze, evaluate, and solve environmental protection problems.

c) Team collaboration and communication: Be able to play a role in the team and effectively communicate environmental awareness and perspectives with others.

Attitudes and awareness:

a) Environmental awareness: Possess a high level of environmental awareness, pay attention to environmental issues, and care about our planet.

b) Environmental responsibility: Possess a sense of social responsibility, actively participate in environmental protection activities, and contribute to environmental protection.

c) Self-reflection: Be able to reflect on one's behavior's impact on the environment and actively improve.

Practical behavior:

a) Environmental behavior: Actively participate in environmental protection actions in daily life, such as resource conservation and low-carbon living.

b) Social participation: Participate in environmental protection organizations and activities, promoting the development of environmental protection causes.

c) Knowledge dissemination: Spread environmental knowledge and concepts to others, raising others' environmental awareness.

This study evaluates teaching effectiveness of environmental literacy education based on fuzzy comprehensive evaluation. First, according to the evaluation index system of environmental literacy education teaching effectiveness, an evaluation factor set is constituted. A set of evaluation comments, such as excellent, good, average, and poor, is set for each evaluation factor, constituting a comment set. Let I represent the evaluation factor set of environmental literacy education teaching effectiveness, and I characterize the fuzzy set composed of various influencing factors affecting the teaching effectiveness of environmental literacy education, satisfying $I=(i_u)$, $u=1,2,...,b$. Let C represent the comment set, characterizing the collection of evaluation results corresponding to each evaluation index given by the evaluator, satisfying $C=(c_k)$, $k=1,2,...,b$.

According to the actual teaching situation, establish membership function relationships between each evaluation factor and the comments in the comment set, and construct a fuzzy relation matrix. The membership function is a value between 0 and 1, indicating the degree of membership of the evaluation factor on the comments. Let the membership relation between i_u in I and c_k in C be represented by e_{uk}, then:

$$e_{uk}=\begin{cases}1, z<s\\ \left(\dfrac{z-s}{n-s}\right)^k, s<z\le n\\ 0, z>n\end{cases}$$

$$e_{uk}=\begin{cases}1, z\ge s\\ \left(\dfrac{z-s}{n-s}\right)^k, n\le z<s\\ 0, z<n\end{cases}$$

$$e_{uk}=\begin{cases}0, z\le s\\ \dfrac{z-s}{n-s}, s\le z\le n\\ 1, n\le z\le v\\ \dfrac{f-z}{f-v}, v<z\le f\\ 0, z>f\end{cases}$$

$$e_{uk}=\begin{cases}0, z\le s\\ \dfrac{z-s}{n-s}, s<z\le n\\ \dfrac{v-z}{v-n}, n\le z\le v\\ 0, z>v\end{cases} \tag{1}$$

$$E=\begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1b} \\ e_{21} & e_{22} & \cdots & e_{2b} \\ \cdots & \cdots & \cdots & \cdots \\ e_{l1} & e_{l2} & \cdots & e_{lb} \end{bmatrix} \tag{2}$$

Assign weights to each evaluation factor according to the importance of the evaluation factors, forming a weight vector. Then, perform matrix operations on the fuzzy relation matrix and the weight vector to obtain the fuzzy evaluation vector. This study uses the analytic hierarchy process (AHP) to determine the weights of the indicators, and the second-level indicators of the index system need to undergo weight synthesis. Suppose the weight vector synthesized by the secondary indicators is represented by S, then the fuzzy evaluation vector $N=S \bullet E$ using the most widely used $MM(\bullet,+)$ logical operation model.

Based on the membership values in the fuzzy evaluation vector, apply the weighted average principle to calculate the comprehensive evaluation value of each evaluation factor. Finally, according to the comprehensive evaluation value, conduct an overall evaluation of the teaching effectiveness of environmental literacy education. To achieve the ranking and selection of the evaluation objects, further sum up the ranks of each level of the environmental literacy education teaching effectiveness evaluation index system based on the weighted average principle. Suppose the rank of environmental literacy education teaching effectiveness is represented by b, and the membership degree of the result vector belonging to the bth level is represented by n_b. The undetermined coefficient (j=1 or j=2) is represented by J, and in this study, 1 is taken. The percentile interval median of the bth level is represented by z_b. The fuzzy comprehensive evaluation result L of the teaching effectiveness of environmental literacy education can be obtained by calculating the following formula:

$$L=\frac{\sum_{1}^{b} n_b^j \cdot z_b}{\sum_{1}^{b} n_b} \tag{3}$$

3. CONSTRUCTION OF ENVIRONMENTAL LITERACY EDUCATION KNOWLEDGE MODEL

Environmental literacy involves multiple disciplinary fields. Constructing an environmental literacy education knowledge model helps integrate educational resources, ensuring the systematic and comprehensive nature of teaching content. It also promotes interdisciplinary integration and fosters communication and cooperation among disciplines. The environmental literacy education knowledge graph focuses on knowledge systems related to environmental protection and sustainable development, which has unique focus and characteristics compared to other knowledge graphs. In terms of content, the environmental literacy education knowledge graph focuses on knowledge related to environmental protection and sustainable development, such as environmental issues, ecological protection, resource utilization, and circular economy. The target population is mainly school teachers and students, aiming to cultivate students' environmental awareness, skills, and behavior through education. The educational goal is to promote sustainable development in schools and improve the environmental literacy of teachers and students.

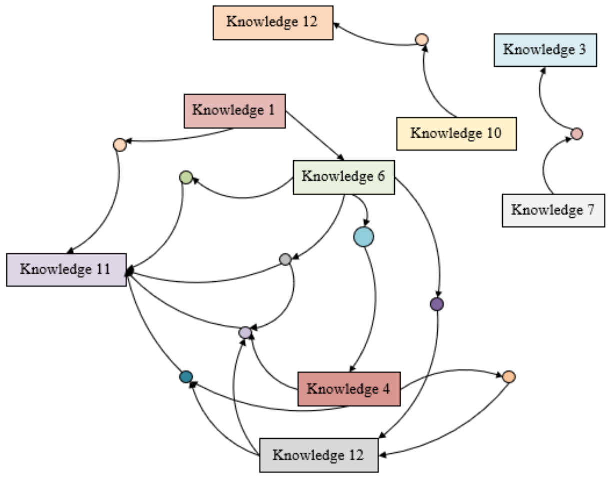

Figure 1. Schematic diagram of course knowledge model construction

This study designs a course knowledge model based on the stored knowledge points and educational relationships in the environmental literacy education knowledge graph that promotes sustainable school development. Figure 1 shows the schematic diagram of the course knowledge model construction. Clarifying the logical relationships between knowledge points helps teachers optimize teaching resources and develop reasonable teaching plans and strategies. At the same time, the environmental literacy education knowledge graph focuses on environmental protection and sustainable development. The design of the course knowledge model helps improve students' environmental awareness and literacy, thereby promoting sustainable development in schools. In the environmental literacy education knowledge graph, this study defines the knowledge points and their associated relationships as follows.

A learning path refers to the process of learners studying knowledge points in a knowledge graph in a specific order. An effective learning path helps learners better understand and master knowledge points and their associated relationships. Suppose any two educational entities in the environmental literacy education knowledge graph that promotes sustainable school development are represented by ED_u and ED_k. The existence of a learning path between these two educational entities can be characterized by the following expression:

$$\begin{cases} (ED_u, ED_k)=1; ED_u, ED_k \in EJH \\ (ED_u, ED_k)=0; ED_u, ED_k \in EJH \end{cases} \tag{4}$$

Knowledge point association types refer to the categories of associations between different knowledge points in the knowledge graph. Common association types include causal relationships, logical relationships, and similarity relationships. The distance between the knowledge points and the target knowledge points in the environmental literacy education knowledge graph that promotes sustainable school development is represented by JL. The B-order neighboring knowledge point is defined as a knowledge point with a distance of b from the target knowledge point that promotes sustainable school development. Then, the degree of association between knowledge points can be calculated using the following formula:

$$JL=b \tag{5}$$

The degree of knowledge point association refers to the closeness of the association between knowledge points in the knowledge graph, which can be represented by weight values. The larger the weight value, the higher the degree of association. Suppose the number of knowledge point associations is represented by *GL*, and the number of knowledge point associations for each educational relationship in the environmental literacy education that promotes sustainable school development is represented by *B*(*EEr*). Then, the following definition formula exists:

$$GL = \sum_{EEr}^{5} B(EEr) \tag{6}$$

4. RECOMMENDATIONS FOR ENVIRONMENTAL LITERACY EDUCATION RESOURCES TO PROMOTE SUSTAINABLE SCHOOL DEVELOPMENT

The recommendation of environmental literacy education resources aims to provide appropriate learning and teaching materials for students and teachers to promote sustainable school development. By recommending environmentally related educational resources, students and teachers can learn more about environmental issues, ecological protection, and other related knowledge, which will enhance their environmental awareness. At the same time, the recommendation of environmental literacy education resources contributes to improving the overall environmental level of the school and promoting the school's sustainable development in areas such as energy, resources, and facilities.

This study applies user knowledge transfer-based recommendation methods to the context of promoting sustainable school development through environmental literacy education resource recommendations. Figure 2 shows the algorithm flow of the environmental literacy education resource recommendation for promoting sustainable school development. Through user knowledge transfer, the valuable information from users' knowledge and experience in other fields can be utilized to enrich the recommendation system's accuracy and coverage. In the context of environmental literacy education resource recommendations for promoting sustainable school development, the source domain and target domain of students' resource ratings can be understood as follows. The source domain refers to the existing knowledge and interest areas of students, where their ratings and feedback on educational resources can provide valuable information for the recommendation system. The target domain refers to the field of environmental literacy education resources, where students need to improve their environmental awareness, skills, and behavior. By analyzing students' ratings and feedback in the source domain, the recommendation system can uncover their latent needs and interests, thereby providing personalized resource recommendations in the target domain (environmental literacy education field). This helps to increase students' attention and participation in environmental issues, promoting sustainable school development.

The user knowledge transfer-based recommendation method adopted first requires calculating student similarity and target domain ratings, followed by student latent feature ranking and updating the student feature matrix. The purpose of calculating student similarity is to identify students with similar interests and knowledge in the source domain.

Assuming that the rating of student *g* for the source domain environmental literacy education resource project *u* is represented by $_{i}e_{gu}$, the rating of student *f* for the source domain environmental literacy education resource project *u* is represented by e_{fu}, the average rating of student *g* for the source domain environmental literacy education resource project is represented by $\bar{e}_f$, and the average rating of student *f* for the source domain environmental literacy education resource project is represented by $\bar{e}_f$. *Pearson* similarity is used to calculate the similarity of students when recommending environmental literacy education resources:

$$SIM(g,f) = \frac{\sum_{u \in U_g \cap U_f} \left(e_{gu} - \bar{e}_g\right) \times \left(e_{fu} - \bar{e}_f\right)}{\sqrt{\sum_{u \in U_g \cap U_f} \left(e_{gu} - \bar{e}_g\right)^2} \times \sqrt{\sum_{u \in U_g \cap U_f} \left(e_{fu} - \bar{e}_f\right)^2}} \tag{7}$$

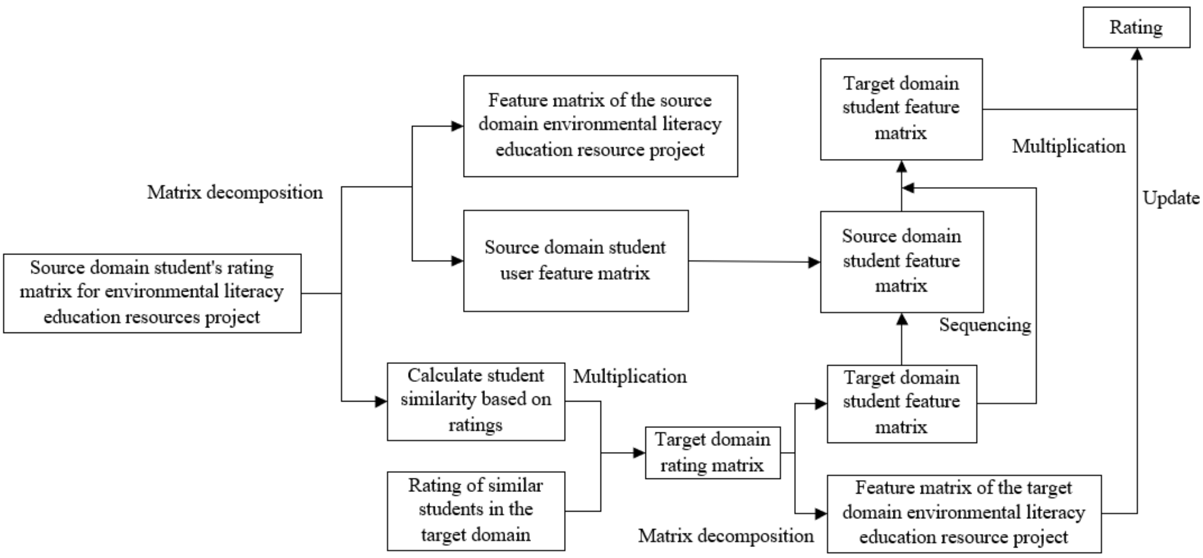

Figure 2. Algorithm flow of environmental literacy education resource recommendation for promoting sustainable school development

In order to obtain more accurate similarity calculation results, assume that the total number of environmental literacy education resource projects rated by student g and student f in the source domain is represented by U_{gf}, and the total number of educational resources evaluated by the two students in the source domain is represented by YTO. Introduce the following calculation:

$$XSD(g,f)=\frac{\left|U_{gf}\right|}{Y_{TO}} \tag{8}$$

By multiplying Formula 1 and Formula 2, a more accurate similarity calculation result can be obtained:

$$SIM_i(g,f)=\frac{\sum_{u\in U_g\cap U_f}\left(e_{gu}-\bar{e}_g\right)\times\left(e_{fu}-\bar{e}_f\right)}{\sqrt{\sum_{u\in U_g\cap U_f}\left(e_{gu}-\bar{e}_g\right)^2}\times\sqrt{\sum_{u\in U_g\cap U_f}\left(e_{fu}-\bar{e}_f\right)^2}}\times\frac{\left|U_{gf}\right|}{Y_{TO}} \tag{9}$$

One of the key steps in a recommendation system is predicting students' ratings of educational resources in the target domain. The significance of calculating target domain ratings lies in predicting students' ratings of educational resources in the target domain (environmental literacy education field) based on their ratings, interests, and knowledge in the source domain, as well as information from other similar students. If there are no similar student users in the source domain, the rating matrix needs to be filled. Assume that the value to be filled is represented by A_{SC}, the similarity value between students is represented by $SIM_i(g,f)$, and the rating value of similar students for environmental literacy education resource projects in the target domain is represented by e. The following formula gives the predicted value of the target domain rating when the similarity is between [0.4,1].

$$A_{SC}=SIM_i(g,f)\times e \tag{10}$$

Using the results of environmental literacy education teaching effectiveness evaluation as part of the students' latent features can help the recommendation system better understand students' needs and performance in environmental literacy education. This study divides the evaluation results into multiple dimensions (such as knowledge mastery, practical ability, attitude and values, etc.) and includes these dimensions in the students' latent feature vectors. In this way, when calculating similarity and predicting ratings, the recommendation system can fully consider students' teaching effectiveness evaluation results.

User latent feature sequencing refers to analyzing students' ratings and behavioral data in the source domain in the recommendation system, and mining students' latent features (such as interest preferences, knowledge structure, etc.). The significance of this step is to convert students' ratings and behavioral data into more easily understood and processed latent features, providing a basis for subsequent recommendation calculations. At the same time, by mining latent features, a better understanding of students' needs and interests can be achieved, thus providing more accurate environmental literacy education resource recommendations. Figure 3 shows an example of feature matrix update.

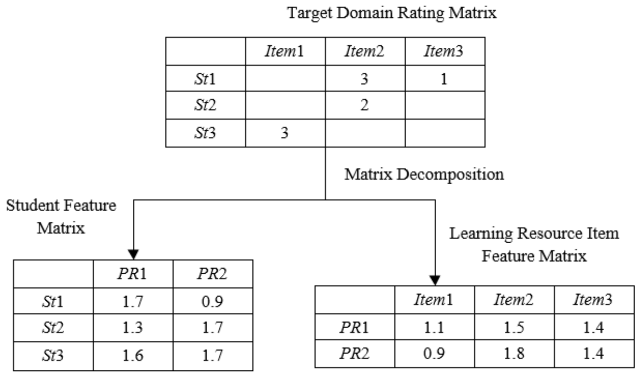

Figure 3. Schematic diagram of feature matrix update

In this study, the user feature matrix of students in the source domain and the feature matrix of environmental literacy education resource projects are generated based on the *Funk-SVD* model matrix decomposition, as well as the student user feature matrix and environmental literacy education resource project feature matrix in the target domain. *Funk-SVD* uses mean square error as the loss function, and the objective function is given by the following formula:

$$\arg\min_{o^*,w^*}\sum_{(i,u)\in b}\left(e_{iu}-w_u^Y o_i\right)^2+\eta\left(\left\|o_i\right\|^2+\left\|w_u\right\|^2\right) \tag{11}$$

Assume that a hyperparameter is represented by η, the student user feature matrix is represented by O, and the environmental literacy education resource project feature matrix is represented by W. The derivatives of the above formula are:

$$\frac{\partial K}{\partial O_i}=-2\left(e_{iu}-w_u^Y o_i\right)w_u+2\eta o_i \tag{12}$$

$$\frac{\partial K}{\partial w_u}=-2\left(e_{iu}-w_u^Y o_i\right)o_i+2\eta w_u \tag{13}$$

The *Funk-SVD* model matrix decomposition algorithm uses gradient descent to solve parameters, and the iterative formulas for gradient descent are:

$$o_i=o_i+\beta\left[\left(e_{iu}-w_u^T o_i\right)w_u-\eta o_i\right] \tag{14}$$

$$w_u=w_u+\beta\left[\left(e_{iu}-w_u^T o_i\right)o_i-\eta w_u\right] \tag{15}$$

Through the above steps, the final O and W can be obtained.

The recommendation system needs to continuously update students' feature information based on new ratings and behavior data to maintain the timeliness and effectiveness of recommendation results. The significance of updating the student user feature matrix lies in adjusting and updating students' latent features and similarity information based on the latest ratings and behavior data in the source and target domains. This helps capture changes in student needs and interests, ensuring that the recommendation system can always provide suitable environmental literacy education resource recommendations for students.

In order to adjust the order of latent features in the source and target domains based on the similarity of students' latent features, it is necessary to establish a feature mapping relationship between the source and target domains for each student based on the calculated similarity. This can be achieved through maximum similarity matching or other matching algorithms. According to the feature mapping relationship, adjust the order of latent features in the student user feature matrix of the source and target domains to keep them consistent. Specifically, swap the rows in the target domain student user feature matrix to make it consistent with the order of the source domain student user feature matrix. After adjusting the order of latent features in the source and target domains, the recommendation model can be retrained to fully utilize the similarity information between the source and target domains during knowledge transfer and recommendation calculations.

Assuming that a certain latent feature of a student in the source domain is represented by YY_j, and a certain latent feature of a student in the target domain is represented by MBY_r. The cosine similarity calculation method shown in the following formula can be used to measure the similarity of students' latent features:

$$SIM = \frac{YY_j MBY_r}{\left\|YY_j\right\| \cdot \left\|MBY_r\right\|} \tag{16}$$

Assuming that a certain latent feature of a student in the source domain is represented by YY_j, and a certain latent feature of a student in the target domain is represented by MBY_r.

After ordering the latent features, the student user feature matrices in the source and target domains are obtained. The next step is to update the target domain's student user feature matrix by applying the source domain's student user feature matrix, which facilitates knowledge transfer. This means that the rating, interest, and knowledge information of students in the source domain can be used to assist in the recommendation calculations in the target domain. This is particularly important for the target domain with insufficient rating information (cold start problem) and helps improve the accuracy of recommendations. Assume that the updated user feature of student f in the target domain is represented by $MBY_{f,q}{}^i$, and the number of environmental literacy education resource project ratings given by the student in the source domain is represented by $B_{u\in a}e^a_{f,u}$, satisfying $B_{u\in a}e^a_{f,u}+B_{u\in a}e^a_{f,u}$. The following update formula is then derived:

$$\begin{aligned} MBY_{f,q}{}^{i} &= \frac{\underset{u\in a}{B} e^a_{f,u}}{\underset{u\in a}{B} e^a_{f,u} + \underset{u\in y}{B} e^y_{f,u}} \times YY_{f,q} \\ &+ \frac{\underset{u\in y}{B} e^y_{f,u}}{\underset{u\in a}{B} e^a_{f,u} + \underset{u\in y}{B} e^y_{f,u}} \times MBY_{f,q} \end{aligned} \tag{17}$$

$$e = OW \tag{18}$$

5. EXPERIMENTAL RESULTS AND ANALYSIS

Figures 4-6 show the recommendation accuracy, recall, and $F1$ values of different recommendation algorithms. As shown in Figure 4, the matrix factorization algorithm has accuracy values of 0.27, 0.28, 0.27, and 0.26 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the accuracy of the matrix factorization algorithm fluctuates slightly with the increase in recommendation list size but remains stable at a relatively low level. This suggests that the matrix factorization algorithm may have certain limitations in processing these data. The association rule mining algorithm has accuracy values of 0.28, 0.32, 0.315, and 0.305 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the accuracy of the association rule mining algorithm shows an increasing trend followed by a decline as the recommendation list size increases, but overall, it is better than the matrix factorization algorithm. This suggests that the association rule mining algorithm has certain advantages in processing these data but still has room for improvement. The algorithm proposed in this study has accuracy values of 0.32, 0.34, 0.35, and 0.325 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the accuracy of the proposed algorithm shows an increasing trend followed by a slight decline as the recommendation list size increases, and it is better than the other two algorithms in all list sizes. This suggests that the proposed algorithm has a good performance in processing these data, with relatively high recommendation accuracy.

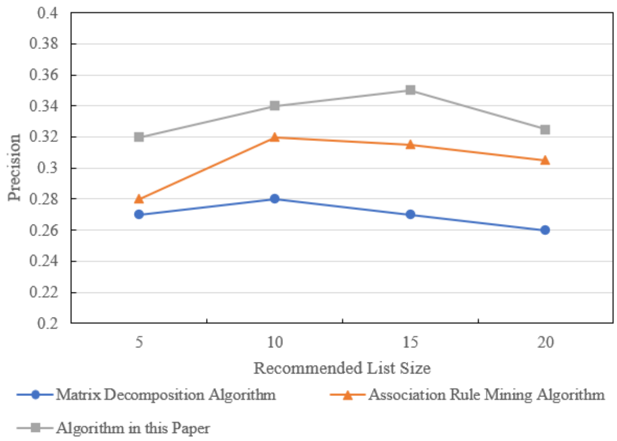

Figure 4. Recommendation accuracy of different recommendation algorithms

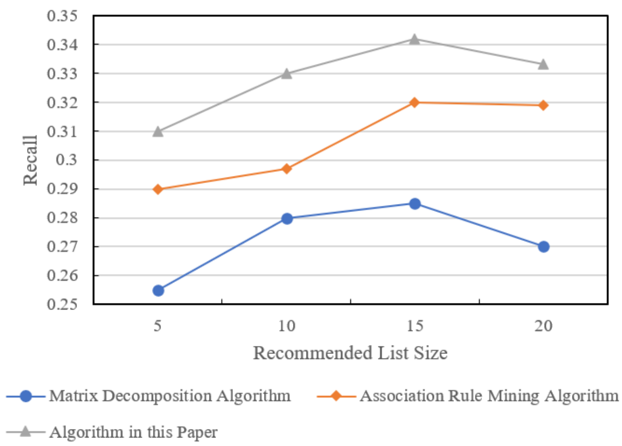

Figure 5. Recall of different recommendation algorithms

As shown in Figure 5, the matrix factorization algorithm has recall values of 0.255, 0.28, 0.285, and 0.27 for recommendation list sizes of 5, 10, 15, and 20, respectively.

This indicates that the recall of the matrix factorization algorithm shows an increasing trend followed by a decline as the recommendation list size increases, but overall, it is relatively low. This suggests that the matrix factorization algorithm may have certain limitations in processing these data, and its ability to find relevant resources needs to be improved. The association rule mining algorithm has recall values of 0.29, 0.297, 0.32, and 0.319 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the recall of the association rule mining algorithm shows an increasing trend followed by a stabilization as the recommendation list size increases, and it is overall better than the matrix factorization algorithm. This suggests that the association rule mining algorithm has certain advantages in processing these data but still has room for improvement. The proposed algorithm has recall values of 0.31, 0.33, 0.342, and 0.333 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the recall of the proposed algorithm shows an increasing trend followed by a slight decline as the recommendation list size increases, and it is better than the other two algorithms in all list sizes. This suggests that the proposed algorithm has a good performance in processing these data, achieving a relatively high recall in finding relevant resources.

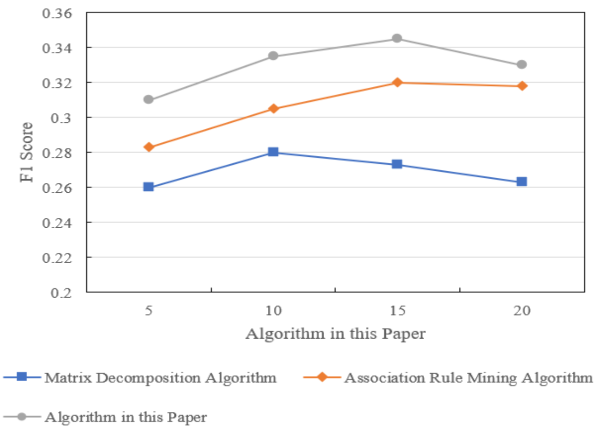

Figure 6. $F1$ values of different recommendation algorithms

As shown in Figure 6, the matrix factorization algorithm has $F1$ values of 0.26, 0.28, 0.273, and 0.263 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the $F1$ value of the matrix factorization algorithm shows an increasing trend followed by a decline as the recommendation list size increases, but overall, it is relatively low. This suggests that the matrix factorization algorithm may have certain limitations in processing these data, and its ability to consider both accuracy and recall needs to be improved. The association rule mining algorithm has $F1$ values of 0.283, 0.305, 0.32, and 0.318 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the $F1$ value of the association rule mining algorithm shows an increasing trend followed by a stabilization as the recommendation list size increases, and it is overall better than the matrix factorization algorithm. This suggests that the association rule mining algorithm has certain advantages in processing these data but still has room for improvement. The proposed algorithm has $F1$ values of 0.31, 0.335, 0.345, and 0.33 for recommendation list sizes of 5, 10, 15, and 20, respectively. This indicates that the $F1$ value of the proposed algorithm shows an increasing trend followed by a slight decline as the recommendation list size increases, and it is better than the other two algorithms in all list sizes. This suggests that the proposed algorithm has a good performance in processing these data, achieving a relatively high $F1$ value, which effectively balances both accuracy and recall.

Based on the data presented in Table 1, an analysis of the evaluation of environmental literacy education based on teaching effectiveness can be conducted. Scores for interdisciplinary knowledge, environmental problem analysis, environmental skills, self-reflection, environmental behavior, and community participation were relatively high, indicating that students demonstrated strong abilities in various aspects of environmental literacy, such as understanding environmental issues from a multidisciplinary perspective, problem-solving skills, and active participation in environmental activities. These high effectiveness indicators suggest that teaching methods and curriculum design in these areas were successful in effectively enhancing students' environmental literacy. Scores for basic environmental knowledge, teamwork and communication, environmental responsibility, and knowledge dissemination were in the moderate effectiveness range, indicating that students' performance in these areas was satisfactory but there is still room for improvement. To enhance teaching effectiveness in these areas, schools can adjust teaching strategies, such as incorporating more case studies related to environmental issues, increasing the practicality of the curriculum, and focusing on cultivating students' teamwork and responsibility. Scores for problem-solving ability, environmental awareness, and environmental behavior were relatively low, indicating that students' performance in these areas needs to be strengthened through measures such as strengthening practical teaching, guiding students to pay attention to environmental issues through environmental theme activities, and encouraging students to participate in environmental actions to integrate environmental concepts into daily life.

Table 1. Evaluation of environmental literacy education based on teaching effectiveness

Sub-Indicators	High Effectiveness	Moderate Effectiveness	Low Effectiveness	Total
Basic Environmental Knowledge	0.62514	0.51428	0.63521	0.65248
Interdisciplinary Knowledge	0.81529	0.81629	0.76259	0.73625
Environmental Problem Analysis	0.80362	0.80362	0.83514	0.81436
Environmental Skills	0.82417	0.82517	0.80625	0.80625
Problem-Solving Ability	0.40625	0.50469	0.51427	0.54179
Teamwork and Communication	0.53824	0.53417	0.73629	0.61425
Environmental Awareness	0.26152	0.30625	0.35241	0.36258
Environmental Responsibility	0.64378	0.51824	0.52814	0.51427
Self-Reflection	0.91524	0.83629	0.73629	0.86925
Environmental Behavior	0.86341	0.81427	0.35241	0.83614
Community Participation	0.90258	0.80326	0.82653	0.91528
Knowledge Dissemination	0.71625	0.76295	0.72519	0.73615

Table 2. School development ratings in different dimensions under different levels of teaching effectiveness of environmental literacy education

Energy efficiency category	Knowledge teaching and cognitive development	Attitude cultivation and value quality	Behavioral training and skill improvement	Campus environment and cultural construction	Social influence and public participation	Comprehensive evaluation value
High efficiency	I	III	IV	III	V	VI
Moderate efficiency	VI	II	VI	V	IV	III
Low efficiency	IV	V	IV	II	VI	V
Total	III	II	IV	VI	II	III

Table 3. Evaluation value of each dimension of school development under different teaching effectiveness of environmental literacy education

Energy efficiency category	Knowledge teaching and cognitive development	Attitude cultivation and value quality	Behavioral training and skill improvement	Campus environment and cultural construction	Social influence and public participation	Comprehensive evaluation value
High efficiency	0.06253	0.03628	0.01583	0.06392	0.01574	0.12629
Moderate efficiency	0.04175	0.08575	0.03629	0.05741	0.03523	0.16254
Low efficiency	0.03621	0.05142	0.04855	0.03524	0.06151	0.19253
Total	0.01588	0.06235	0.06175	0.01586	0.02741	0.10514

Based on the teaching effectiveness of environmental literacy education, this study will consider the promotion of school development from the following five dimensions: 1) knowledge imparting and cognitive development; 2) attitude cultivation and value shaping; 3) behavioral training and skill improvement; 4) campus environment and cultural construction; 5) social influence and public participation.

Table 2 shows the rating of each dimension of school development under different teaching effectiveness of environmental literacy education. It can be seen that under high efficiency, knowledge imparting and cognitive development (*I*), behavioral training and skill improvement (*IV*) and social influence and public participation (*V*) are rated higher. This shows that under high-efficiency teaching, students can master environmental knowledge well, have strong environmental skills and behavioral performance, and the school has achieved good results in social influence and public participation. Attitude cultivation and value quality (III) and campus environment and cultural construction (III) are at a moderate level under high efficiency. This means that under high-efficiency teaching, there is still room for improvement in students' environmental attitudes, values, campus environment and cultural construction.

Under moderate efficiency, attitude cultivation and value quality (II) and social influence and public participation (*IV*) are rated higher. This shows that under moderate-efficiency teaching, students' environmental attitudes, values, and the school's social influence and public participation have achieved certain results, but there is still room for improvement. Knowledge imparting and cognitive development (*VI*), behavioral training and skill improvement (*VI*) and campus environment and cultural construction (*V*) are rated lower under moderate efficiency. This shows that the development effects in these areas need to be improved under moderate-efficiency teaching.

Under low efficiency, campus environment and cultural construction (*I*) are rated higher. This means that under low-efficiency teaching, the school has achieved certain results in campus environment and cultural construction. Knowledge imparting and cognitive development (*IV*), attitude cultivation and value quality (*V*), behavioral training and skill improvement (*IV*) and social influence and public participation (*VI*) are rated lower under low efficiency. This shows that the development effects in these areas are poor under low-efficiency teaching, and the school needs to adjust teaching strategies promptly.

Table 3 shows the evaluation value of each dimension of school development under different teaching effectiveness of environmental literacy education. According to the data in the table, under high efficiency, the evaluation value of knowledge teaching and cognitive development (0.06253), attitude cultivation and value quality (0.03628), and campus environment and cultural construction (0.06392) is higher. This shows that under highly efficient teaching, students perform better in these aspects, and the teaching strategy and curriculum of schools are more successful in these aspects. The evaluation value of behavioral training and skill improvement (0.01583) and social influence and public participation (0.01574) is lower. This indicates that the development effects in these areas need to be improved under high-efficiency teaching. Schools need to adjust teaching strategies and course settings to improve students' performance in these areas.

Under moderate efficiency, the evaluation value of attitude cultivation and value orientation (0.08575) and campus environment and cultural construction (0.05741) is higher. This shows that under moderate-efficiency teaching, students' performance in these areas is still acceptable, but there is still room for improvement. Schools can further improve the development effectiveness in these areas by improving teaching methods and course content. The evaluation value of knowledge teaching and cognitive development (0.04175), behavioral training and skill improvement (0.03629) and social influence and public participation (0.03523) is lower. This shows that under moderate-efficiency teaching, students' performance in these areas needs to be improved. Schools need to adjust teaching strategies and course settings in a timely manner to improve students' performance in these areas.

Under low efficiency, the evaluation value of attitude cultivation and value orientation (0.05142) and social influence and public participation (0.06151) is higher. This means that under low-efficiency teaching, students' performance in these areas is still acceptable, but there is still room for improvement. Schools can further improve the development effectiveness in these areas by improving teaching methods and course content. The evaluation value of knowledge teaching and cognitive development (0.03621), behavioral training and skill improvement (0.04855) and campus environment and cultural construction (0.03524) is lower. This shows that the development effects in these areas are poor under low-efficiency teaching, and schools need to adjust teaching strategies and course settings in a timely manner to improve students' performance in these areas. The results of Table 2 and Table 3 are basically consistent.

6. CONCLUSION

In order to explore the correlation between environmental literacy education and sustainable school development, this study carried out related research. It gives the evaluation index system of teaching effectiveness of environmental literacy education, and expounds the method process of evaluating the teaching effectiveness of environmental literacy education based on fuzzy comprehensive evaluation method. Based on the knowledge points and the educational relationship between knowledge points in the environmental literacy education knowledge map for promoting sustainable school development, the curriculum knowledge model of environmental literacy education is constructed. The recommendation method based on user knowledge transfer is applied to the scenario of recommending environmental literacy education resources to promote sustainable school development, and the method process is given. Combined with experiments, the recommendation accuracy, recall rate and F1 value of different recommendation algorithms are given. It is verified by comparison that this algorithm has better performance in processing these data.

The evaluation of environmental literacy education based on teaching effectiveness is analyzed. The rating results of each dimension of school development under different teaching effectiveness of environmental literacy education are given. The rating of each dimension of school development under high efficiency, moderate efficiency and low efficiency is given. Relevant conclusions on the correlation between environmental literacy education and sustainable school development are drawn.

Overall, this study explored the correlation between environmental literacy education and sustainable school development from multiple perspectives. It provides a reference for using environmental literacy education to promote sustainable development of schools. However, there are still some limitations in this study. Follow-up research can further explore the implementation path of environmental literacy education in schools from a practical perspective.

REFERENCES

[1] Sokac, M., Pufek, P., Milardic, M., Mihaljevic, B., Puskaric, S., Zagar, M. (2021). Work-in-progress: Data science framework for environmental protection education. In 2021 IEEE Global Engineering Education Conference (EDUCON), Vienna, Austria, pp. 1296-1300. https://doi.org/10.1109/EDUCON46332.2021.9453975

[2] Ma, G., Chen, J. (2018). Teaching reform with industry and education integration of eco-environmental protection majors for better serving rural revitalization strategies. In IOP Conference Series: Earth and Environmental Science, 199(2): 022023. https://doi.org/10.1088/1755-1315/199/2/022023

[3] Ozerova, N.V., Zavyalova, A.A., Korolev, I.V., Zvonkova, N.V., Sidorenko, A.V. (2020). Using visualization in the educational process in the direction of environmental protection. In 2020 V International Conference on Information Technologies in Engineering Education (Inforino), Moscow, Russia, pp. 1-5. https://doi.org/10.1109/Inforino48376.2020.9111860

[4] Zorrilla-Pujana, J., Rossi, S. (2014). Integrating environmental education in marine protected areas management in Colombia. Ocean & Coastal Management, 93: 67-75. https://doi.org/10.1016/j.ocecoaman.2014.03.006

[5] Kotis, K., Papasalouros, A., Nikitakos, N.V. (2009). Supporting decision making in maritime environmental protection with a knowledge-based education and awareness approach. In AIAI Workshops, pp. 280-290.

[6] Santana Salomao, J.M. (2001). Revealing the marambaia: a participative experience on environmental education with small rural producers inside the environmental protection area of itacare coast - serra grande. Tecbahia Revista Baiana De Tecnologia, Language: Portuguese, 16(1): 97-106.

[7] Palmos, D., Papavasileiou, C., Papakitsos, E.C., Vamvakeros, X., Mavrakis, A. (2021). Enhancing the environmental programmes of secondary education by using web-tools concerning precaution measures in civil protection: The case of Western Attica (Greece). Safety Science, 135: 105117. https://doi.org/10.1016/j.ssci.2020.105117

[8] Xie, Y., Chen, Z., Tang, H., Boadu, F., Yang, Y. (2023). Effects of executives' pro-environmental education and knowledge sharing activities on eco-friendly agricultural production: Evidence from China. Journal of Cleaner Production, 395: 136469. https://doi.org/10.1016/j.jclepro.2023.136469

[9] Malyshev, V.S., Fedorova, E.V., Borovkova, A.M., Startsev, V.A. (2020). Education of labor protection and environmental engineering specialists based on neural network data processing technology. In 2020 V International Conference on Information Technologies in Engineering Education (Inforino), Moscow, Russia, pp. 1-4. https://doi.org/10.1109/Inforino48376.2020.9111733

[10] Simionescu, M., Horvathova, Z., Kovshun, N., Kushnir, N. (2020). Social media, sustainability, and environmental protection in sustainable education. In E3S Web of Conferences, 208: 09002. https://doi.org/10.1051/e3sconf/202020809002

[11] Nguyen, H.T., Pham, T.T.H., Nguyen, H.T. (2021). Organizing experiences-based learning activities "making bio-products for environmental protection" in STEM Education in high schools. In Journal of Physics: Conference Series, 1835(1): 012059. https://doi.org/10.1088/1742-6596/1835/1/012059

[12] de Pontes, S.R.S., Guimarães, C.C., Oliver Cornwell, T., Krelling, A.P. (2022). Perceptions on the effectiveness of environmental education programs as environmental licensing tools for port-related enterprise in Brazil. Environmental Management, 70(4): 565-580. https://doi.org/10.1007/s00267-022-01682-z

[13] Ahmadi, A., Abbaspour, M., Afkhami Namin, N. (2021).

Assessment of Iran academic environmental education needs with climate change approach. International Journal of Environmental Science and Technology, 18: 49-56. https://doi.org/10.1007/s13762-020-02850-6

[14] Weng, T.S. (2019). Life-changing digital education on environmental protection and LOHAS. In Proceedings of the 3rd International Conference on Education and Multimedia Technology, pp. 50-54. https://doi.org/10.1145/3345120.3345197

[15] Tadena, M.T.G., Salic-Hairulla, M.A. (2021). Local-based lesson on hydrologic cycle with environmental education integration: Designing learners ideas through STEM. In Journal of Physics: Conference Series, 1835(1): 012035. https://doi.org/10.1088/1742-6596/1835/1/012035

[16] Gong, T., Wang, J. (2023). A data-driven smart evaluation framework for teaching effect based on fuzzy comprehensive analysis. IEEE Access, 11: 23355-23365. https://doi.org/10.1109/ACCESS.2023.3253379

[17] Singh, A.K., Singh, B. (2022). Role of education in sustainable development goals. ECS Transactions, 107(1): 11685. https://doi.org/10.1149/10701.11685ecst

[18] Khovrak, I., Sivyakova, G., Khovrak, I. (2022). Management of lifelong education projects for sustainable development. In 2022 IEEE 4th International Conference on Modern Electrical and Energy System (MEES), Kremenchuk, Ukraine, pp. 1-4. https://doi.org/10.1109/MEES58014.2022.10005703