International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 7451-7461

https://doi.org/10.70517/ijhsa464644

The Application of a Collaborative Education Model Combining Ideological and Political Courses with Architectural Professional Courses in Housing Planning Education

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Abstract: This study addresses the issue of insufficient integration of ideological and political elements in housing planning education by proposing a personalized teaching system design based on the concept of collaborative education. By identifying ideological and political elements within regional architectural culture, the study constructs a curriculum-based ideological and political education pathway. A teaching system incorporating interest modeling, dynamic updates, and intelligent recommendations is developed, with the heap sort algorithm selected to implement personalized teaching resource recommendations. Empirical research indicates that, in terms of knowledge tracking, the completeness of learners' knowledge systems improved by 47.8%, average grades increased by 19.7 points, and the rate of excellence rose by 30.3%. In terms of personalized recommendations, learners at different levels saw significant improvements in average grades during the course, particularly for beginners and intermediate learners, with an average increase of 6.82%.

Index Terms Ideological and political education courses, Architecture major, Housing planning education, Personalized teaching system, Heap sort algorithm, Student interest modeling

I. Introduction

In the current context of globalization and technological advancement, education not only focuses on the transmission of professional skills and knowledge but also emphasizes the cultivation of comprehensive qualities and values [1], [2]. Against this backdrop, integrating ideological and political elements into professional courses has become a necessary exploration in educational innovation and practice. Especially in the field of architectural engineering technology, cultivating students' sense of social responsibility, ethical values, and sustainable development concepts is of critical importance [3]. As a key field for cultivating future urban builders, architectural programs not only need to impart professional knowledge and skills but also focus on enhancing students' ideological and moral qualities and shaping their values [4], [5]. Integrating ideological and political education elements into architectural program curricula is both a requirement for fulfilling the fundamental task of cultivating virtue and fostering talent and an important pathway for enhancing students' comprehensive qualities and promoting the healthy development of the architectural industry [6]-[8]. Implementing a collaborative education model between ideological and political courses and architecture-related courses can help guide students in forming correct cognitive and value pursuits, enabling them to clarify their life direction and become individuals with a sense of social responsibility [9]-[11]. Additionally, students can recognize the basic rules and moral requirements of society through education, which contributes to maintaining social harmony and stability [12], [13].

Currently, due to the deepening of China's urbanization process and the transformation of urban development models, China's urban development has entered a new phase of transformation characterized by the upgrading and renovation of existing urban areas and the adjustment of new urban development structures. People's demands for housing have also shifted toward a pursuit of “living quality” [14], [15]. Housing planning education should be grounded in the contemporary context, with a focus on residents' lifestyles and the behavioral needs of families. Therefore, promoting the application of a collaborative education model between ideological and political courses and architectural professional courses in housing planning education is both a key response to contemporary social challenges and a necessary pathway for cultivating future citizens.

This paper first systematically outlines the process for identifying the core elements of course-based ideological and political education and proposes a personalized teaching system design. It focuses on establishing a model for students' initial interests and a dynamic update mechanism for interest vectors, designing a personalized recommendation module. Using real-world data, it demonstrates the process for recommending personalized teaching resources. Based on three publicly available knowledge tracking datasets, the paper evaluates the knowledge tracking performance of the proposed algorithm and verifies its application effectiveness using actual data. Through comparative experiments, the paper tests the personalized recommendation performance of the algorithm. By combining ideological and political education and housing planning courses, the paper verifies that the proposed algorithm has a positive impact on improving the academic performance of learners at all levels.

II. Design of a personalized teaching system that integrates ideological and political courses with architecture courses

II. A.2.1 Identifying the core elements of course-based ideological and political education

The course-based ideological and political education teaching approach is illustrated in Figure 1. The course revolves around the core issues of the socialist education system: “What kind of people should be cultivated? How should they be cultivated? For whom should they be cultivated?” By leveraging the distinctive features of the architecture program, the course clarifies the key content of course design, establishes a clear ideological and political education objective orientation, and identifies the ideological and political elements embedded in regional culture that can inform design and creation. The five new development concept - “innovation, green development, openness, coordination, and shared prosperity”—serve as the fundamental guiding principles for ideological and political education in the architecture program. The program actively serves and integrates into the green, low-carbon, livable, and business-friendly development needs of urban and rural construction, with the goal of cultivating composite, innovative, and application-oriented urban and rural construction talent. The “Housing Planning” social practice course and the “Regional Architectural Design Special Topics” design course form a teaching loop through knowledge systems, skill cultivation, and design thinking. Essentially, these two courses represent the dialectical unity of “protection” and “development,” ‘tradition’ and “modernity,” demonstrating the program's overall coherence and interconnectedness. Based on housing planning surveying practice, the third-year architecture course design teaching explores the “1331” course ideological and political education implementation path, which is rooted in the “local characteristics,” promotes Chinese excellent traditional culture, and establishes the three design concepts of “environmental perspective, cultural perspective, and ecological perspective” as the main thread. This approach comprehensively enhances students' confidence in regional architectural culture. Using “local culture” as a medium, this approach aims to protect and inherit regional architectural cultural heritage, driving the creative transformation and innovative development of outstanding regional architectural cultural heritage.

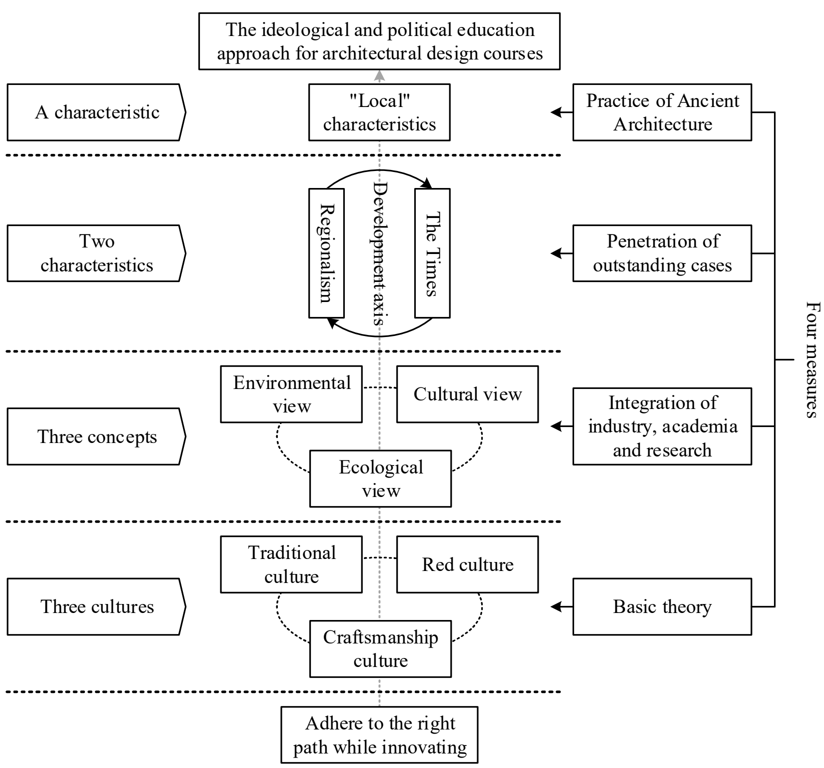


Figure 1: Teaching path of ideological and political education in curriculum

II. B.Design of a personalized teaching system

In the context of higher education in the new era, the deep integration of ideological and political education with professional education has become an important means of implementing the fundamental task of cultivating virtue and fostering talent. This paper takes the “Housing Planning” course in the architecture major as its research object and explores the application mechanisms and implementation paths of the collaborative education model between ideological and political courses and professional courses in teaching practice.

II. B. 1) Establishment of an initial student interest model

In this module, the system will convert the initial student interest information collected by the interest collection module into a structured, computable, formalized vector space model using certain methods.

Based on the information collection method of the interest collection module, the algorithm for establishing the interest model designed in this paper is as follows:

(1) When students only select professional keywords without any descriptive text, keyword k_i in the student interest model is the professional keyword k_i selected by the student. Since each professional keyword is considered by experienced teachers to be an important knowledge point in this chapter, this system considers each professional keyword to be of equal importance in this chapter. If the total number of professional keywords extracted by teachers for a chapter is N, each selected professional keyword is assigned a weight of $1/N$; otherwise, it is 0. A N-dimensional vector $\{...<k_i,0>...<k_j,1/N>...\}(1\le i,j\le N)$ can be constructed, where k_i represents the professional keywords selected by the student, and k_j represents the professional keywords not selected.

(2) When students do not select professional keywords but only provide a description of their interests, the student interest model is constructed using the following method:

1) Perform word segmentation on the student description content and perform preliminary filtering of noise words, i.e., remove $f_j=<k_j,w_j>,1\le j\le n$, k_j as keywords, and w_j as the number of times k_j appears in the student's interest description;

2) Perform synonym processing on each keyword $k_j(1\le j\le n)$ in the results of step a. If there is a corresponding professional keyword $k_i(1\le i\le N)$ (N is the total number of professional keywords extracted in this article) in the synonym database that is synonymous with k_j, then replace k_j in the n-dimensional vector with k_i.

3) Then, merge similar keywords in the n-dimensional vector, i.e., merge all f_i s with the same keywords. If there are (k,w_p) and (k,w_q) in the n-dimensional vector, merge them into (k,w_p+w_q) to obtain the m-dimensional interest vector (m<=n).

4) Count the total number of times all professional keywords appear in the m-dimensional vector R, construct a N-dimensional vector, and replace the weight w_j value of professional keywords that appear in the student's description with w_j/R. The weight value of professional keywords that do not appear is 0.

5) If the N-dimensional vector is empty, the system considers that the student is extremely unfamiliar with the content of this chapter, and the system will provide a brief introduction to the content of this chapter and then ask the student to make a selection or provide a description again.

(3) When students have selected professional keywords and described their interests, the system considers that the professional keyword k_i selected by the student reflects the knowledge points they wish to learn. If the subsequent interest description includes the same keyword as professional keyword k_i, it is considered to be a further explanation of the content related to professional keyword k_i. The steps for constructing the initial interest model for students are as follows:

1) First, construct two N-dimensional vectors h_1 and h_2 separately according to the methods described in 1 and 2 above;

2) Combine h_1 and h_2 to construct a N-dimensional interest vector $h_3=\{<k_1,w_1^{'}>...<k_j,w_j^{'}>...<k_N,w_N^{'}>\}$, where $k_j(1\le j\le N)$ are professional keywords and $w_j^{'}(1\le j\le N)$ are keyword weight values in the comprehensive student interest vector, and calculate their values using the following formula (1).

$$w_j^{'}=\frac{w_j(h_1)+w_j(h_2)}{\sqrt{\sum_{j=1}^{N}[w_j(h_1)+w_j(h_2)]}} \tag{1}$$

where $w_j(h_1)$ represents the weight value of keyword k_j in vector h_1; $w_j(h_2)$ represents the weight value of keyword k_j in vector h_2; N represents the total number of professional keywords extracted by the teacher in this chapter; and the denominator is the normalization factor.

II. B. 2) Updating Student Interest Vectors

When students first begin a new chapter of study, student interest management collects information about their interests to construct an initial interest model, which is then used to recommend learning texts that most closely match their learning interests. However, as the learning process progresses, students' learning interests will change. Therefore, this paper proposes a method for updating the student interest model based on implicit feedback information.

Psychologists have found that a person's interest in learning can be reflected through some related actions he takes when browsing learning texts, such as searching, marking bookmarks, saving, dwell time, and dragging the scroll bar. In this article, we only study a few commonly used behaviors that best represent students' interest in the current learning text. These behaviors are: the number of times the scroll bar is dragged (L_d), the time spent reading the learning text (T_d), saving the learning text (S_d), printing the learning text (P_d), following links to similar learning texts (F_d), and copying the content of the learning text (C_d). All these behaviors to some extent reflect the students' interest in the current learning text D. Therefore, in order to distinguish the different levels of interest each behavior represents for the students, this paper sets a weight of w_v for each of the above behavioral actions, and the sum of all the weights is 1. Therefore, by recording the above-mentioned behaviors of the student when learning text d, the system inferences the degree to which the student is interested in Text d R_d. The calculation formula is as follows:

$$R_d = \sum_{v \in C} W_v f_v(d) \tag{2}$$

Among these, $C = \{L_d, T_d, S_d, P_d, F_d, C_d\}$ and W_v are the weight values assigned to behavior v, $f_v(d)$ is a binary value function, and if a student exhibits any of the behaviors in *C* for *d*, the corresponding function value is 1. However, behavior L_d must reach a certain number of times, and T_d must be greater than t (threshold) for the corresponding function values $f_{L_d}(d)$ and $f_{T_d}(d)$ to be 1, otherwise they are 0. Finally, the value obtained from the above formula, R_d, will be used to update the student's interest vector.

The update steps are as follows:

(1) Use formula (2) to calculate the student's interest level R_d in the currently recommended learning text d;

(2) Replace the original value of $w_i(h)$ with $w_i^l(h)$ calculated using the following formula for k_i in the student interest vector:

$$w_i^{'}(h) = \frac{w_i(h) + k^* R_d^* w_i(d)}{\sqrt{\sum_{i=1}^{N} [w_i(h) + k^* R_d^* w_i(d)]^2}}, k \in (0,1) \tag{3}$$

Among them, the denominator is the normalization factor.

II. B. 3) Implicit updating of student interest vectors

As the learning process progresses, students' learning interests will change. This change manifests itself in two ways: on the one hand, early interests will gradually fade over time; on the other hand, changes in students' interests can be tracked and identified by analyzing various learning behaviors during the learning process. Therefore, based on the above two aspects, this paper proposes a method for implicitly updating the student interest model.

(1) Update based on time decay

We know that during the learning process, when we have not yet fully mastered a particular knowledge point or concept, our interest in it is relatively strong, and the level of interest is high. However, as we gradually master this knowledge point, our interest in it will diminish over time. Therefore, after each user logs back into the system, the interest vector for that user is updated with time decay. The update algorithm for the interest weight w_i corresponding to the keyword k_i as it changes over time is defined as follows:

$$w_i^{'} = \frac{\delta}{\delta + (T - (t_{login} - t_{quit}) - t_i)} \times w_i, t_i^{'} = T \tag{4}$$

Among these, w_i' is the updated interest weight value, t_i' is the updated interest node time, and δ is the adjustment coefficient. T is the current system time, t_{login} is the time when the user logged into the system this time, t_{quit} is the time when the user last logged out of the system, t_i is the last modification time of the interest node, and w_i is the last weight of the interest node.

The meaning of this equation is: a student user's interest in a particular keyword decays over time as learning progresses. The larger the adjustment coefficient δ, the slower the interest decay rate; the smaller the adjustment coefficient δ, the faster the interest decay rate. To account for situations where a student user logs out of the system and does not engage in learning for an extended period but their interest remains unchanged, the variables t_{login} and t_{quit} are designed to eliminate the interference of the period during which the user was logged out and not engaged in learning on the interest weight.

(2) Update based on browsing behavior

Psychological studies have shown that as the learning process progresses, students' interests shift and are reflected through a series of learning actions during the process. Through long-term observation, we selected seven behaviors for study: saving, copying, printing, multiple clicks, scroll bar movements, mouse clicks, and browsing time. These behaviors to some extent reflect students' interest in the document, and thus contribute to the development of an interest model. Therefore, this paper calculates the contribution values of these behaviors to determine students' interest levels and refine the interest model. Considering the differences in reading time and the number of operations required due to varying document lengths, this paper adopts a contribution value calculation method based on the number of characters, incorporating two variables: the current document's character count $W_{current}$ and the average character count of documents already read by the user $W_{average}$. The specific algorithm is as follows:

1) The initial value of the operation command contribution value $V_{command}$ is 0. When the user clicks the save or print command, $V_{command} = V_{command} + M_{save}$, where M_{save} is the save reward factor; When the user clicks to open the same document multiple times, $V_{command} = V_{command} + M_{copen} \times k$, where M_{open} is the open reward factor, and k is the number of clicks.

2) Scroll bar contribution value $V_{scroll} = \left(\frac{S_{arrent}}{W_{current}} - \frac{S_{average}}{W_{average}} \right) \times M_{scroll}$, where $S_{current}$ is the number of scrolls the user has made on the current page, $S_{average}$ is the average number of page scrolls for that user, and M_{scroll} is the scroll reward factor.

3) Click contribution value $V_{click} = \left(\frac{C_{current}}{W_{current}} - \frac{C_{average}}{W_{average}} \right) \times M_{click}$ where $C_{current}$ is the number of clicks on the current page, $C_{average}$ is the average number of clicks per page for the user, and M_{click} is the click reward factor.

4) Browsing time contribution value $V_{time} = \left(\frac{T_{current}}{W_{current}} - \frac{T_{average}}{W_{average}} \right) \times M_{time}$, where $T_{current}$ is the user's browsing time on the current page, $T_{average}$ is the average browsing time for pages the user has previously visited, and M_{time} is the time reward factor.

5) When a user performs a copy operation on certain content in a document, it indicates that the user has a relatively high level of interest in the copied text, so the copied text segment is handled separately.

Based on the above four contribution values, the total contribution value $V_d(u)$ of document d to user u's interest update is obtained, which is the level of interest of user u in document d, as shown in the following formula:

$$V_d(u) = V_{command} + V_{scroll} + V_{click} + V_{time} \tag{5}$$

In the above algorithm, it is necessary to record the average browsing actions of each user and the average number of words per article. We adopt the following method: during the first learning process of each student user, we obtain and record the average value of the first N documents browsed. In this process, we only collect four sets of data: the number of scroll bar clicks $S_{current}$, mouse click count $C_{current}$, browsing time $T_{current}$, and current document word count $W_{current}$. After the user has browsed the first N documents, the three average values are calculated using formula (6), and the average word count is obtained using formula (7).

$$X_{average} = \frac{\sum_{i=1}^{N} X_{current}^{i}}{N}, X \in (S,C,T) \quad (6)$$

$$W_{average} = \frac{\sum_{i=1}^{N} W_{current}^{i}}{N} \quad (7)$$

In the student's subsequent learning process, after browsing through M documents, the average value is updated using formulas (8) and (9).

$$X_{average} = \frac{X_{average} + \frac{\sum_{i=1}^{M} X_{current}^{i}}{M}}{2}, X \in (S,C,T) \quad (8)$$

$$W_{average}^{'} = \frac{W_{average} + \frac{\sum_{i=1}^{M} W_{current}^{i}}{M}}{2} \quad (9)$$

After obtaining the current text d 's $V_d(u)$ for student user u and the segment of text copied by the user, update the student's interests according to the following steps:

1) Extract the spatial vector of the current document d:

$Resource(d) = \{(k_1(d), w_1(d)), (k_2(d), w_2(d)), \cdots, (k_n(d), w_n(d))\}$;

where $k_i(d)$ is the i th keyword in document d, and $w_i(d)$ is the weight value corresponding to $k_i(d)$. Using the same weight calculation method, perform word frequency statistics on the user-copied text segment segment to obtain the spatial vector of the text segment segment:

$Resource(seg) = \{(k_1(seg), w_1(seg)), (k_2(seg), w_2(seg)), \cdots, (k_m(seg), w_m(seg))\}$;

2) Calculate the transition weight value $w_i^{'}(d) = V_d(u) \times w_i(d)$ corresponding to each keyword. If the keyword $k_i(d)$ appears in the copied text segment segment at position j, then set $w_i^{'}(d) = w_i^{'}(d) + w_j(seg)$; if the keyword $k_i(d)$ does not appear in the copied text segment segment, then add this keyword to the document space transition vector. Thus, the document's space transition vector is obtained as:

$Resource^{'}(d) = \{(k_1(d), w_1^{'}(d)), (k_2(d), w_2^{'}(d)), \cdots, (k_n(d), w_n^{'}(d))\}$ is obtained.

3) Backup the user u 's interest vector $Hobby(u)$ to the interest transition vector $Hobby^{'}(u) = \{f_1^{'}(u), f_2^{'}(u), \cdots, f_n^{'}(u)\}$.

4) Determine whether the keyword $k_i(d)$ in the document space transition vector $Resource^{'}(d)$ exists in the user's current interest vector $Hobby^{'}(u)$. If it does not exist, proceed to step 5; if it exists, proceed to step 6.

5) Add a new node to $Hobby(u)$, i.e.,

$Hobby^{'}(u) = \{f_1^{'}(u), f_2^{'}(u), \cdots, f_n^{'}(u), f_{n+1}^{'}(u)\}$, where $f_{n+1}^{'}(u) = (k_i(d), w_i^{'}(d), T)$, and T is the current time.

6) If the keyword $k_i(d)$ in $Resource^{'}(d)$ and the keyword $k_j(u)$ in $Hobby^{'}(u)$ are the same, then let $Hobby^{'}(u)$ as $f_j^{'}(u) = (k_j(u), w_j^{'}(u), T)$, where $w_j^{'}(u) = w_j(u) + w_i^{'}(d)$, and T is the current time.

7) After merging all keywords in $Resource^{'}(d)$ into $Hobby^{'}(u)$, we obtain a vector with o dimensions, namely $Hobby^{'}(u) = \{(k_1(u), w_1^{'}(u), T), (k_2(u), w_2^{'}(u), T), \cdots, (k_o(u), w_o^{'}(u), T)\}$ and $n \le o$. Since the weight values in the vector are obtained by accumulation, they may exceed 1. Therefore, the weight values in the vector are normalized: $w_i^{'}(u) = \frac{w_i^{'}(u)}{\sum_{i=1}^{m} w_i^{'}(u)}$.

8) Perform dimensionality reduction on the normalized interest transition vector $Hobby^{'}(u)$. First, remove nodes with weights less than or equal to zero. Then, sort the remaining nodes and retain the top 12 keyword nodes with the largest weight values. These replace the user interest vector $Hobby(u)$, i.e., $Hobby(u) = Hobby^{'}(u)$.

II. B. 4) Design of the personalized recommendation module

From experience, we know that student users often do not want documents they have already read to appear in the recommended document list. Furthermore, when the recommended document resources are not unique and are arranged in order from top to bottom, student users generally browse the document titles at the top first. When the top titles catch their interest, they often click to read them. Only after browsing through all the top titles and finding none of them interesting do they move on to browse the titles below. Based on the above two points of common sense, we can make the following improvements to enhance the user learning experience: avoid repeatedly recommending resources that have already been read to users; place document resources that users are more interested in at the top.

To address the issue of duplicate recommendations, we can create a new “read” set $perused(u)$ for each user. When a user clicks to read a document d, we add document d to the set $perused(u)$. When a document d has been added to the current user's read collection $perused(u)$, we do not perform similarity comparisons or recommendation sorting on document d. Instead, we only display the titles of all documents in the collection $perused(u)$ in the user interface.

To address the issue of prioritizing documents of interest, we employ methods such as comparing user interests and document similarity, as well as sorting operations.

(1) Similarity comparison module

After extracting User u's interest vector $Hobby(u)$, how can we recommend documents that align with the user's interests? To address this issue, we must compare the similarity between the user's interest feature vector and all document resource vectors, selecting the 15 most similar documents to present to the user for selection. In document similarity comparisons based on vector representation methods, commonly used algorithms include the inner product method, the DICE coefficient method, the JACCARD coefficient method, and the cosine coefficient method. To obtain relatively reasonable comparison results, this paper uses the cosine angle for measurement. The interest feature vector $Hobby(u)$ of user u is extracted from the student interest database, and the resource vector $Resource(d)$ of document d is extracted from the learning resource database. The calculation formula is as follows:

$$sim(u,d) = \cos(u,d) = \frac{u \cdot d}{|u||d|} = \frac{\sum_{i=1}^{n} w_i(u) \times w_i(d)}{\sqrt{\sum_{i=1}^{n} w_i^2(u) \times \sum_{i=1}^{n} w_i^2(d)}} \tag{10}$$

Among them, $w_i(u)$ and $w_i(d)$ are the weight values corresponding to keyword i for student user u and document resource d, respectively.

(2) Sorting module

By comparing the similarity between interest vectors and document vectors through the similarity comparison module, we obtain the similarity values between each document and the user's current interests. We can assume that the higher the similarity, the more closely aligned the document is with the user's interests, indicating a higher level of interest and making it a resource the user is more likely to want to learn from. Therefore, we can sort the similarity values in descending order to obtain a sequence of documents ranked by similarity and recommend the corresponding documents to student users.

For the following two reasons, we do not need to sort all document resources suitable for user learning.

1) Due to the sequential nature of students' browsing process, i.e., students typically browse title information from top to bottom. When they encounter a document of interest, they will click to read it. Only when they are not interested in any of the title information on the current page will they click to browse the next page.

2) At any given moment, the number of students currently learning is too high, which inevitably leads to excessive server computational load and network transmission load.

Considering the above, we can initially recommend only the few documents with the highest similarity and arrange them in order on the first page. Only after the user clicks to view the next page is it necessary to sort the resources on the next page.

We can describe this sorting problem as follows: in a set of unsorted arrays, find the top N largest numbers, sort these N largest numbers, and then perform a secondary sort on the array after removing these N numbers. Among the more commonly used sorting algorithms, we chose heap sort as the core algorithm for our design.

III. Analysis of the application of personalized teaching systems

III. A. Personalized Teaching Resource Recommendation Process

This section analyzes personalized teaching resource recommendations using the "Housing Planning" course taught at the School of Architecture of a certain university in the 2023-2024 academic year as an example. The scoring data was collected using the Likert scale from 62 third-year students participating in the pilot of the personalized teaching system, while the access behavior data was obtained from the learning trajectory logs automatically recorded by the system's backend. All data has been anonymized and underwent reliability and validity testing using SPSS 26.0, meeting the data standards required for educational empirical research.

Collaborative filtering recommendations generate a recommendation list for target users based on the opinions of other users. Its core principle is to produce the final recommendation results through the nearest neighbor's ratings. The current user's rating for unrated projects is approximated by the weighted average of the nearest neighbor's ratings for that project. User rating data is shown in Table 1, where rows represent users, columns represent projects, and elements in rows and columns represent users' ratings for projects. From the rating matrix, it can be seen that Student A shows a strong interest in traditional residential protection (5 points), forming a significant gradient difference with housing policy analysis (2 points). Student B, on the other hand, shows a significant preference for technology-related projects, with the highest ratings for green building technology (5 points) and building energy-saving design (4 points). This differentiation provides the data foundation for collaborative recommendations.

Table 1: User Rating Data

	Protection of Traditional Dwellings	Analysis of Housing Policies	Green building technology	Energy-saving design of buildings
A1	5	2	3	4
A2	3	3	5	4
A3	4	4	3	3
A4	4	3	5	2
A5	4	5	3	4
A6	3	3	4	5
A7	4	3	4	4
A8	5	4	3	4
...	...	...	...	...

This paper systematically determines the recommended content based on the "learner-learner" relationship. Based on the similarity of learners' interests, the system recommends knowledge points that other learners with similar interests to the target learner are interested in. The number of times users access knowledge points is shown in Table 2. Student A's cultural heritage (7 times) and policy regulations (9 times) exhibit a high-frequency pattern. When Student A studies related topics, the system prioritizes recommending resources frequently accessed by the student, achieving precise integration of ideological and political elements with professional knowledge.

Table 2: Number of User Visits to Knowledge Points

Project	Cultural inheritance	Policies and regulations	Low-carbon technology	Energy-saving structure
A1	7	9	5	4
A2	6	5	8	7
A3	5	6	8	8
A4	7	8	5	4
A5	9	8	6	4
A6	10	9	7	7
A7	4	3	6	8
A8	5	2	8	9
...	...	...	...	...

III. B. Analysis of the effectiveness of knowledge tracking

III. B. 1) Performance Testing

The experimental data required for this study relies on three publicly available knowledge tracking datasets: ASSISTments2015, ASSISTments2022, and Statics2023. The performance comparison results of different recommendation algorithms are shown in Table 3, with the data representing the average values of each algorithm across the three datasets. The algorithm proposed in this paper demonstrates significant advantages across all evaluation metrics. It achieves an accuracy rate of 0.358, representing a 3.5% improvement over the next-best NMF algorithm. The recall rate of the proposed algorithm is 0.301, with an NDCG of 0.402, and the project coverage rate is 13.8% higher than that of the NMF algorithm. In terms of system response time, the proposed algorithm requires only 44ms, validating its efficiency in practical educational applications.

Table 3: Performance Comparison Results of different Recommendation Algorithms

Algorithm type	Precision	Recall	NDCG	Item coverage rate	Average response time/ms
UserCF	0.284	0.261	0.328	0.142	93
DKT	0.328	0.274	0.342	0.158	81
SVD	0.337	0.282	0.359	0.169	68
NMF	0.346	0.289	0.371	0.174	57
The proposed	0.358	0.301	0.402	0.198	44

The AUC values of different algorithms on the three datasets are shown in Figure 2. The algorithm proposed in this paper maintains optimal performance on all datasets, with the most outstanding performance on the Statics2023 dataset, achieving an AUC value of 0.89.

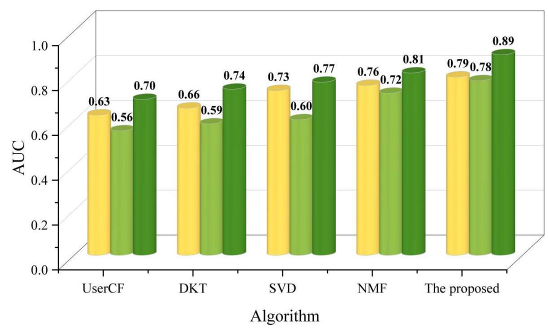


Figure 2: AUC values of different algorithms on the three datasets

III. B. 2) Application Effects

One architecture student was selected as the research subject, with all data sourced from system-generated records and standardized assessments during actual teaching processes. A comparative analysis of changes in learner behavior and learning outcomes before and after the system implementation is presented in Table 4. The results demonstrate significant effectiveness of the system application: the average single learning session duration increased from 36 minutes to 61 minutes, knowledge point mastery speed improved by 50%, and learning resource completion rate reached 98.6%. Analysis of knowledge point coverage shows that the completeness of learners' knowledge systems improved by 47.8%, and their ability to understand the interconnections between knowledge points significantly enhanced. Test score analysis indicates that after using the personalized recommendation system, the average score of learners increased by 19.7 points, and the rate of excellent scores increased by 30.3%. In-depth analysis reveals that the system's intelligent recommendation mechanism effectively stimulates learners' motivation to learn by precisely matching learning resources to reduce learning difficulty, enhance learning efficiency and experience, and create a positive learning cycle.

Table 4: Results of Changes in Learning Outcomes

Evaluation index	Before	After	Extent of increase
Study duration (minutes per session)	36	61	69.4%
Completion rate of learning resources	58.8%	98.6%	39.8%
Integrity of the knowledge system	44.5%	92.3%	47.8%
The speed of knowledge point mastery (relative value)	100%	150%	50%
Average examination score	69.7	89.4	19.7
Excellence rate	34.2%	64.5%	30.3%

III. C. Analysis of the effectiveness of personalized recommendations

MOOC datasets typically contain various pieces of information related to online courses, such as student registration information, course content, learning behavior, and assessment scores. The multidimensional data structure of these datasets enables researchers to analyze the effectiveness of online education and learners' behavioral patterns from multiple perspectives.

In this study, a subset of 1,000 participants was selected from the MOOCs dataset. During the sampling process, factors such as learners' geographical distribution, age groups, and fields of study were fully considered to ensure that the subset could maximally reflect the learning characteristics and performance of learners from diverse backgrounds, thereby providing a representative foundational data framework for subsequent experiments.

III. C. 1) Performance Testing

The comparison results of the performance metrics of the recommendation algorithms are shown in Table 5. In terms of algorithm performance improvement, compared with the UserCF algorithm, the algorithm proposed in this paper improved the AUC, ACC, Precision, and Recall metrics by 15.0%, 15.1%, 15.9%, and 16.8%, respectively. This comprehensive performance advantage verifies the effectiveness of integrating knowledge tracking and learner behavior modeling.

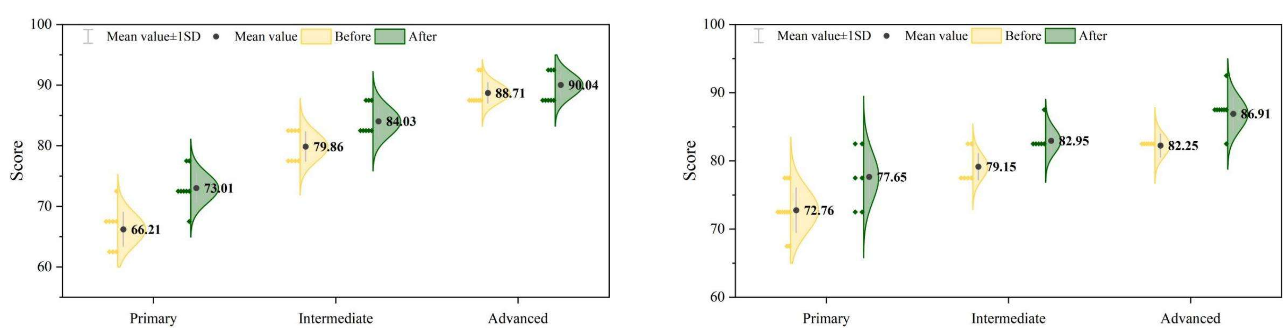
Table 5: Comparison Results of Performance Index Parameters

Algorithm type	AUC	ACC	Precision	Recall
UserCF	0.733	0.793	0.772	0.755
DKT	0.745	0.801	0.786	0.764
SVD	0.761	0.812	0.818	0.788
NMF	0.774	0.824	0.827	0.794
The proposed	0.843	0.913	0.895	0.882

III. C. 2) Application Effects

This paper collected feedback data from 122 users who used online courses based on the recommendation algorithm proposed in this paper during the fall semester of 2024 through an online learning platform. According to the survey questionnaire, 103 users (84.43%) indicated that the recommendation results were highly relevant to their learning needs and course objectives. In terms of the presentation of recommendation results, over 90% of users found the recommended learning resource list to be concise and clear, making it easy to browse and select learning resources, aligning with their daily learning habits. Analysis of users' learning behavior data on the platform revealed that after implementing the new recommendation algorithm, the average weekly learning duration increased by 3 hours compared to the same course in the fall semester of 2023, and the completion rate of course resources improved by 20.1%.

In terms of academic performance, by comparing the distribution of grades before and after using the recommended learning resources for learners at three levels—beginner, intermediate, and advanced—in the courses of Ideological and Political Education and Housing Planning, the changes in course grades for learners at different levels before and after using the algorithm are shown in Figures 3(a–b). For learners at different levels, the average grades improved significantly after using the recommended algorithm, particularly for beginner and intermediate learners, with an average increase of 6.82%, indicating that the recommended algorithm has a positive impact on improving the academic performance of learners at all levels.



(a) Ideological and political education (b) Housing planning

Figure 3: Course scores of learners at different levels before and after use

IV. Conclusion

This study constructed a collaborative education system between ideological and political courses and architectural professional courses, achieving an organic integration of professional knowledge transmission and value guidance.

In terms of knowledge tracking, the algorithm proposed in this paper achieved an accuracy rate of 0.358, which is 3.5% higher than the second-best NMF algorithm. The recall rate was 0.301, the NDCG reached 0.402, and the project coverage rate was 13.8% higher than that of the NMF algorithm. In terms of system response time, the algorithm requires only 44 milliseconds. The system's application effectiveness is also significant: the average single learning session duration for learners increased from 36 minutes to 61 minutes, knowledge point mastery speed improved by 50%, and learning resource completion rate reached 98.6%. Knowledge point coverage analysis shows that the completeness of learners' knowledge systems improved by 47.8%. Test score analysis indicates that after using the personalized recommendation system, the average score of learners increased by 19.7 points, and the excellent rate increased by 30.3%.

In terms of personalized recommendations, compared to the UserCF algorithm, the proposed algorithm achieved improvements of 15.0%, 15.1%, 15.9%, and 16.8% in AUC, ACC, Precision, and Recall metrics, respectively. For learners at different levels, the average scores improved significantly after using the recommendation algorithm compared to before, particularly for beginner and intermediate learners, with an average increase of 6.82%, indicating that the recommendation algorithm has a positive impact on improving the academic performance of learners at all levels.

References

[1] Shan, Y. (2023). Thoughts on promoting the construction of “curriculum ideology and politics” in professional courses of vocational and technical education. Journal of Education and Educational Research, 3, 162-164.

[2] Yanyue, C. (2023). Research on the Ideological and Political Reform of Curriculum in Vocational Colleges from the Perspective of Integration of Industry and Education. education, 6(24), 148-155.

[3] Guo, L., & Liu, R. (2024). Research on Teaching Reform of Architectural Construction Course Based on Curriculum Ideology and Politics for Architecture Major. Journal of Environmental and Building Engineering, 1(1).

[4] Ma, Z. (2023). Research on the Implementation Path of Ideological and Political Education in Civil Engineering and Architecture Major Courses from the Perspective of Critical Thinking. Advances in Educational Technology and Psychology, 7 (17), 131, 138.

[5] Zhao, W., & Yang, Y. (2023, September). Exploration on Ideological and Political Teaching of “Civil Engineering Construction Technology” Course. In 2023 9th International Conference on Humanities and Social Science Research (ICHSSR 2023) (pp. 278-283). Atlantis Press.

[6] Han, L. (2024). Exploration of Ideological and Political Education Reform in Architectural Design Theory Courses: A Case Study of the Principles of Landscape Architecture Design Course. International Journal of New Developments in Education, 6(9).

[7] Liu, Z., Zhang, Q., Chen, L., & Zhang, S. (2024). Research on the Construction of Teaching Cases of Curriculum Ideology and Politics Based on BIM Technology—Taking the “Engineering Valuation” Series of Courses as Examples. Open Journal of Social Sciences, 12(04), 647-654.

[8] Lv, C. (2024, July). Analysis and Practice of Ideological and Political Education in Computer Public Basic Courses in Architecture Universities Based on Machine Learning and Deep Learning. In Proceedings of the 2024 Guangdong-Hong Kong-Macao Greater Bay Area International Conference on Education Digitalization and Computer Science (pp. 75-81).

[9] Zhao, X., & Huang, B. (2025, April). Integrating the Cultural Spirit of the Guangdong-Hong Kong-Macao Greater Bay Area into the Ideological and Political Education in Architecture and Civil Engineering Courses. In 2024 3rd International Conference on Educational Science and Social Culture (ESSC 2024) (pp. 929-938). Atlantis Press.

[10] Huang, W., Ji, F., & Li, Z. (2024, October). Incorporating Ideological and Political Education in Civil Engineering Mechanics Courses. In 2024 8th International Seminar on Education, Management and Social Sciences (ISEMSS 2024) (pp. 160-167). Atlantis Press.

[11] Shang, D., & Guo, J. (2024). Research on the Application and Innovation of Environmental Design in Ideological and Political Work in Universities. Journal of Environmental and Building Engineering, 1(2).

[12] Xu, Y. (2025). Implementation Strategies of Ideological and Political Education in Civil Engineering Testing Courses Oriented by Structural Safety Responsibility. The Educational Review, USA, 9(5).

[13] Shang, L. (2023). Discussion On the Way of Ideological and Political Integration in the Course of Construction Engineering Survey. International Journal of Vocational and Technical Education, 3(3), 14.

[14] Yakob, H., Yusof, F., & Hamdan, H. (2015). Stakeholders’ perception on the effectiveness of housing planning and control in urban areas: A preliminary survey. Procedia-Social and Behavioral Sciences, 168, 289-301.

[15] Mouratidis, K. (2021). Urban planning and quality of life: A review of pathways linking the built environment to subjective well-being. Cities, 115, 103229.