International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 9070-9079

https://doi.org/10.70517/ijhsa463179

# Research on Personalized Course Recommendation System for Civic Education Based on Adaptive Learning Algorithm

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**Abstract** As a new normal under the trend of "Internet+Education", adaptive learning mode is facing the problems of unsuitable resource recommendation and insignificant learning effect while widely popularized. This paper analyzes the learning process of adaptive learning algorithm, makes clear the important components of adaptive learning system centered on learners. Considering the differences in learning styles of different students, the learning style model and learning resource model are constructed successively. By calculating the similarity between students' learning styles and learning resources' learning styles, personalized recommendation based on learning styles is completed. Then we elaborate three personalized resource recommendation algorithms based on learning style filtering recommendation algorithm, collaborative filtering recommendation algorithm, and association rule recommendation algorithm, which adapt to different learning styles in order to recommend resources. Subsequently, the overall framework of the system is designed to form a personalized recommendation system for Civic and Political Education, which consists of three layers: data layer, business layer and user layer. The learning style model is utilized to classify learning styles into four types, namely active and reflective, perceptual and intuitive, visual and verbal, and sequential and global, based on the individual situation of the research subjects. On this basis, the click rate of text resources and video resources recommended by the personalized recommendation system for political thinking education are both above 90.00% and up to 98.71%. It shows that the personalized recommendation system designed in this paper can accurately adapt to the learning preferences and learning styles of the learners, so as to recommend the most compatible learning resources.

**Index Terms** adaptive learning algorithm, personalized resource recommendation, learning style model, civic education

## I. Introduction

Ideological and political education is the primary content of China's spiritual civilization construction and one of the main ways to solve social contradictions and problems [1], [2]. In education and teaching, the ideological and political courses are of great significance in promoting students to form a correct worldview, outlook on life and values, and cultivating qualified socialist builders and successors [3]-[5]. However, there are some problems in the current Civic and Political Education that constrain its effectiveness. With the rapid development of Internet technology, Civic and Political Education is undergoing a profound change driven by technology [6]-[8]. In this change, the personalized course recommendation system for Civic and Political Education based on adaptive learning algorithm comes into being, which provides students with a more efficient and convenient learning experience with its unique learning method and personalized service [9]-[12].

Personalized recommendation and adaptive learning are hot topics in the field of educational technology in recent years [13]. The traditional education model often fails to meet students' individualized learning needs, while the personalized course recommendation system is able to provide students with customized learning resources and learning paths based on their learning habits, interests, ability levels and other factors [14]-[17]. This kind of system can not only improve students' learning efficiency, but also stimulate students' motivation to learn, which has far-reaching significance for the development of the education field [18], [19].

This paper firstly describes in detail the adaptive learning process supported by artificial intelligence technology, and accordingly proposes the framework of personalized learning system. Secondly, it takes the learner as the core, discusses the operation and collaboration process of learning style model and learning resource style model, and demonstrates the personalized recommendation process based on learning style. Then, we analyze the learning style-based filtering recommendation algorithm, collaborative filtering recommendation algorithm and association rule recommendation algorithm. Combining the three personalized recommendation algorithms, design the overall framework of the personalized system, so as to complete the formation of the personalized recommendation system for Civic and Political Education. Finally, the learning style model is used to classify the types of learning styles, and the learning styles of the research subjects are counted. Based on the individual situation of the research subjects, the performance comparison experiment between the designed personalized recommendation system for Civic and Political Education and similar algorithms is carried out.

## II. Adaptive learning process

With the rapid development of Internet technology and multimedia technology, educators are constantly exploring new modes of learning, and learning resources are becoming more and more diversified as a result. Although there are vast learning resources in the network, different learners have different characteristics, and their education levels are also very different, which makes learners troubled in choosing suitable learning resources for themselves, resulting in students' disorientation and redundancy of learning resources. General learning systems that fail to provide resources based on learners' characteristics cannot enhance learners' learning efficiency, making learners remain in a less efficient learning state.

The core of AI education is adaptive recommendation, and the key to adaptive recommendation is to collect and analyze the personal characteristics of each learner and then recommend personalized learning resources for them. Therefore, it is necessary to fully grasp the learner's personal characteristics and education level, and then personalized recommendation accordingly, recommending appropriate learning strategies and learning resources.

The key to collect and analyze learners' personal characteristics is to build a student characteristic model. The system can build a student characteristic model by collecting relevant data, analyzing learners' characteristics and recommending appropriate learning resources to them. Analyzing student characteristics is only the first step, so it is necessary to use collaborative filtering recommendation technology to filter out the learning resources chosen by students with the same level of education.

The adaptive learning system based on personalized recommendation in this study is an already constructed adaptive learning system, which is mainly composed of the following parts. The learner is the object served by the system, and the system needs to obtain the learner characteristic information as the construction factor of the student model, and then analyze the learner data to produce personalized recommendations. Learning resources are used throughout the process.

## III. Construction of Personalized Recommendation System for Civic Education

### *III. A. Personalized recommendation process based on learning styles*

(1) Learning style modeling

Taking the ILS questionnaire test as an example, after a learner has answered all the questions in the questionnaire, the system will represent the answer results in a spatial matrix, the row vectors represent the four dimensions divided by the ILS, and $LS_{i1}$, $LS_{i2}$, and $LS_{i3}$ represent the answer data of the two options as well as the final style tendency, respectively. For example, if a learner chooses 8 $a$ and 3 $b$ in the information processing dimension, the value of $LS_{21}$ is $\frac{8}{11}$, the value of $LS_{22}$ is $\frac{3}{11}$, and $LS_{21} > LS_{22}$ so that $LS_{23}$ has a value of 1, which indicates that the learner's information processing is characterized by a bias toward the perceptual type, and conversely, if $LS_{21} < LS_{22}$, the value of $LS_{23}$ is less than 0, indicating that the learner is characterized by a bias toward the intuitive type of information processing, and if the value of $LS_{23}$ is equal to 0 (when the values of $LS_{21}$ and $LS_{22}$ are $\frac{5}{11}$ and $\frac{6}{11}$ respectively) indicating that the learner is balanced in information processing. The LS matrix is shown in equation (1):

$$LS = \begin{bmatrix} LS_{11} & LS_{12} & LS_{13} \\ LS_{21} & LS_{22} & LS_{23} \\ LS_{31} & LS_{32} & LS_{33} \\ LS_{41} & LS_{42} & LS_{43} \end{bmatrix} \tag{1}$$

(2) Construction of learning style model for learning resources

The data of learning resources style model needs to be constructed based on the data of learners' learning styles. In the learning process, students select resources for learning, and after learning, they need to evaluate each resource, and the evaluation indexes are divided into five items, which are “very satisfied, satisfied, average, dissatisfied, very dissatisfied”. For each resource, the probability value of a certain type in a dimension can be calculated first, such as formula (2), $m$ indicates the number of people who choose to be very satisfied, $n$

indicates the number of people who choose to be satisfied with the option, $P_i$ indicates the probability value of the type corresponding to the learning style of the learner who evaluates to be very satisfied, and $P_j$ indicates the probability value of the type corresponding to the learning style of the learner who evaluates to be satisfied. For example if $P$ denotes the probability value of the information input dimension visual type, then $P_i$ denotes the probability value of the information input dimension visual type of the learner rated as very satisfied and $P_j$ denotes the probability value of the information input dimension visual type of the learner rated as satisfied.

$$P = \frac{\sum_{i=1}^{m} P_i + \frac{1}{3}\sum_{j=1}^{n} P_j}{m+n} \tag{2}$$

According to the above formula can be each dimension value $P_{ij}$ ($i$ value of 1, 2, 3, 4, $j$ value of 1, 2, 3) one by one to find out, each resource needs to find out the value of eight items separately, $P_{i1}$ and $P_{i2}$ will be normalized, and $LS_{i3}$ is found out in a process similar to that of the process of $LS_{i3}$, according to the $P_{i1}$ and $P_{i2}$ to the value of $P_{i3}$, if $P_{i1} > P_{i2}$, the value of $P_{i3}$ is 1, and vice versa, the value of $P_{i3}$ is -1. When $|P_{i1} - P_{i2}| \le \frac{1}{11}$, the $P_{i3}$ has a value of 0. Based on the value of $P_{i3}$, the style data of learning resources is derived, i.e., what is the type of learning resources in each dimension respectively, and the style data of learning resources is shown in Fig. 1.

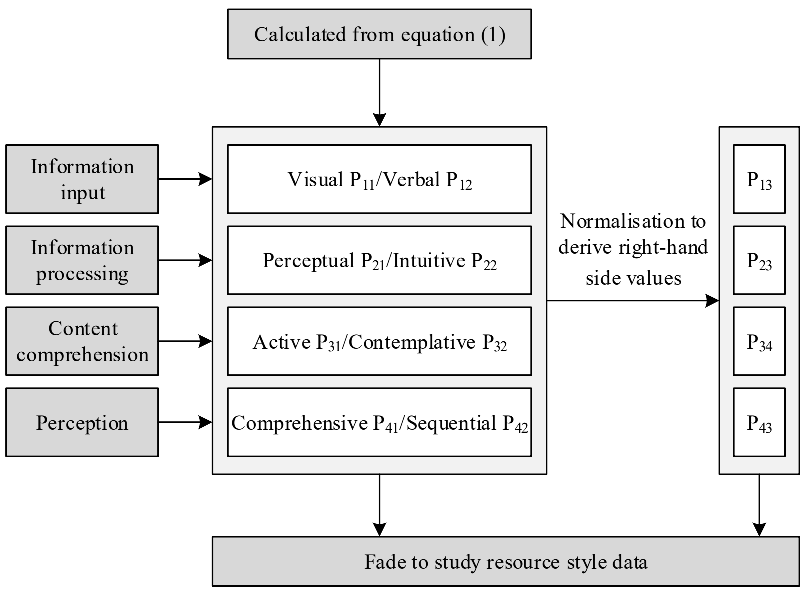


Figure 1: Learning resource style data

(3) Similarity calculation

Using the cosine similarity theorem, the similarity calculation formula of learners' learning style and learning resources' learning style can be derived as in equation (3), where $P_{ij}$ denotes the $j$ th value of the $i$ th dimension of the learning style in learning resources, and $LS_{ij}$ denotes the $j$ th value of the $i$ th dimension of the learners' learning style. Finally, a few resources with the largest degree of similarity between learning styles and learners' learning styles in learning resources are selected for recommendation.

$$\begin{aligned} sim(S,U) = \cos(S,U) &= \frac{S \cdot L}{|S||L|} \\ &= \frac{\sum_{i=1}^{4}\sum_{j=1}^{2} P_{ij} LS_{ij}}{\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} P_{ij}^2}\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} LS_{ij}^2}} \end{aligned} \tag{3}$$

## III. B. Personalized Resource Recommendation Algorithm

### III. B. 1) Recommendation Algorithm Based on Learning Style Filtering

The core idea of the recommendation algorithm based on learning style filtering is to utilize the principle of cosine similarity to calculate the selection of learning resources with a high degree of similarity to the learner's learning style according to Eq. (4) for recommendation.

$$sim_1 = \frac{\sum_{i=1}^{4}\sum_{j=1}^{2} P_{ij} ILS_{ij}}{\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} P_{ij}^2}\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} ILS_{ij}^2}} \tag{4}$$

### III. B. 2) Recommendation Algorithms Based on Collaborative Filtering

The core idea of collaborative filtering based recommendation algorithm is to calculate the learner learning style similarity according to equation (5) to perform recommendation operation, i.e., to recommend the personalized learning resources owned by learners with similar learning styles.

$$sim_2 = \frac{\sum_{i=1}^{4}\sum_{j=1}^{2} ILS_{ij} ILS'_{ij}}{\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} ILS_{ij}^2}\sqrt{\sum_{i=1}^{4}\sum_{j=1}^{2} ILS'^2_{ij}}} \tag{5}$$

### III. B. 3) Recommendation algorithms based on association rules

The core idea of the association rule-based recommendation algorithm is to recommend some learning resources with a larger degree of association to learners according to the characteristics of the intrinsic association of the knowledge points in the learning resources, and further optimize the effect of personalized resource recommendation effectively. The association rule-based recommendation algorithm is illustrated in Figure 2.

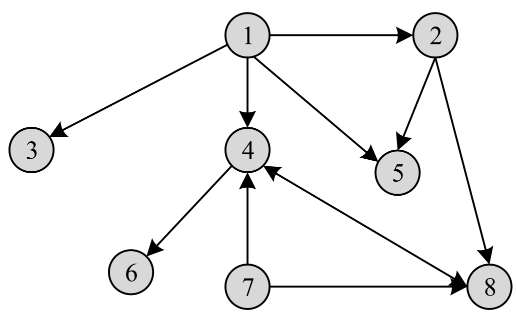


Figure 2: Illustration of recommendation algorithm based on association rules

The knowledge points in the learning resource are related to each other in a certain way, and there is a correlation between knowledge point 1 and 2, 3, 4 and 5, between knowledge point 2 and 5 and 8, and between knowledge point 7 and 4 and 8. When a learner is provided with learning resources for knowledge point 2, the learning resources with higher correlation can be recommended to him/her by calculating the similarity of correlation between knowledge point 2 and other knowledge points.

## III. C. Overall system framework

The online learning resource recommendation system based on adaptive learning mainly adopts a three-layer architecture model, which is divided into data layer, business layer and user layer. The overall system architecture is shown in Figure 3.

According to the three-layer architecture model, the user side can realize the interaction with the database through the business layer, which not only provides a simple front-end interface for the user side, but also facilitates the system to realize the modular decomposition, and lays the foundation for the development and later maintenance of the system.

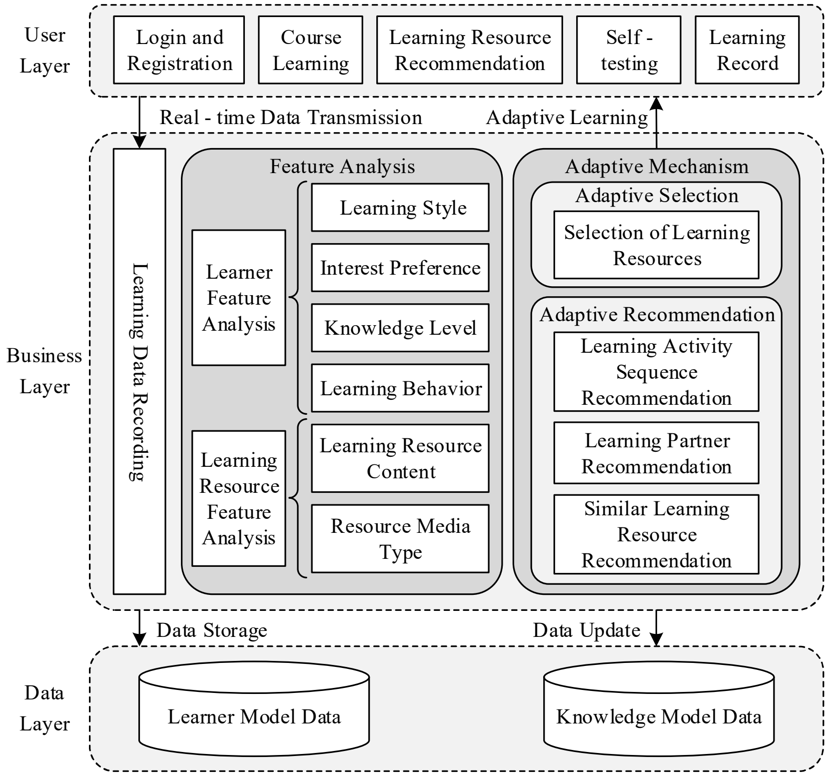


Figure 3: Overall architecture of the system

(1) Data Layer

The data layer is the most basic level in the system architecture, which mainly stores, processes and manages the system data. The data layer of the system in this study stores learner model data and knowledge model data: learner model data includes learner basic information, learning style test, learning behavior records and other data. The knowledge model data includes data such as learning course resources, learning style test scale and test question bank, etc. This layer is responsible for managing and storing the above data.

(2) Business Layer

The business layer is the middle layer of the system architecture, which accepts and processes information from the user layer and transmits it to the data layer for storage and management. This layer is the business logic layer that realizes the core of the online learning resources recommendation system, including the recording of learner behavioral data, the characterization of learners and learning resources, and the pushing of learning resources based on the adaptive recommendation method.

(3) User Layer

The user layer is the outermost layer of the system architecture, which is the interface between the user and the system, and this layer mainly realizes the interaction between the learner and the system and the display of the content. Learners of the online learning resources recommendation system based on adaptive learning can realize the functions of registering and logging in, course learning, learning resources recommendation, independent testing and learning records through the user layer, and the learning data of this layer will be stored in the database, which is convenient for updating and analyzing the data in the database.

## IV. Performance Evaluation of Personalized Recommender System for Civic Education

This chapter uses the proposed learning style model to classify learning styles based on the learning preferences of the research subjects, and to count and organize the learning styles of the research subjects. Based on the learning styles of different learners, the time complexity and resource recommendation click rate application effect comparison between this paper's recommendation algorithm and similar algorithms is carried out.

### *IV. A. Learning styles*

In this section, 110 students from college F were selected for the study to categorize the learning styles as well as the statistics of learning styles.

#### IV. A. 1) Classification of learning styles

Using the learning style model proposed above, learning preferences were categorized according to four dimensions:(A) active vs. reflective, (B) perceptual vs. intuitive, (C) visual vs. verbal, and (D) sequential vs. global. Data on students' learning styles were collected by means of a questionnaire. A Learning Style Scale was designed to assess the four learning style dimensions, which consisted of 56 questions, each of which consisted of choosing one of two options (“a” or “b”). These questions were categorized into 4 groups of 14 questions each based on the different dimensions and scored out of 10. The results of the questionnaire for four randomly selected learners in HEI F are shown in Table 1.

Table 1: Questionnaire results of four random students

| Students | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Active type (Aa) | 8 | 6 | 5 | 9 |
| Reflective type (Ab) | 5 | 7 | 8 | 4 |
| Perceptual type (Ba) | 4 | 9 | 7 | 8 |
| Intuitional type (Bb) | 9 | 4 | 6 | 5 |
| Visual type (Ca) | 3 | 8 | 9 | 7 |
| Verbal type (Cb) | 10 | 5 | 4 | 6 |
| Sequential type (Da) | 10 | 9 | 8 | 2 |
| Global type (Db) | 2 | 3 | 5 | 10 |

#### IV. A. 2) Learning style statistics

Based on the learning style model designed in this paper, the ILS Learning Style Scale was used to investigate the learning styles of 110 students in F colleges and universities. A total of 110 questionnaires were distributed, 100 valid questionnaires were recovered, and the validity rate of the questionnaires was 90.91%. For the purpose of analysis, the 100 students were divided into 20 groups, with a total of 5 students in each group, which were sequentially coded into intervals 1, 2, 3...18, 19, and 20. Among them, the distribution of (A) active and reflective learning style students is shown in Figure 4.

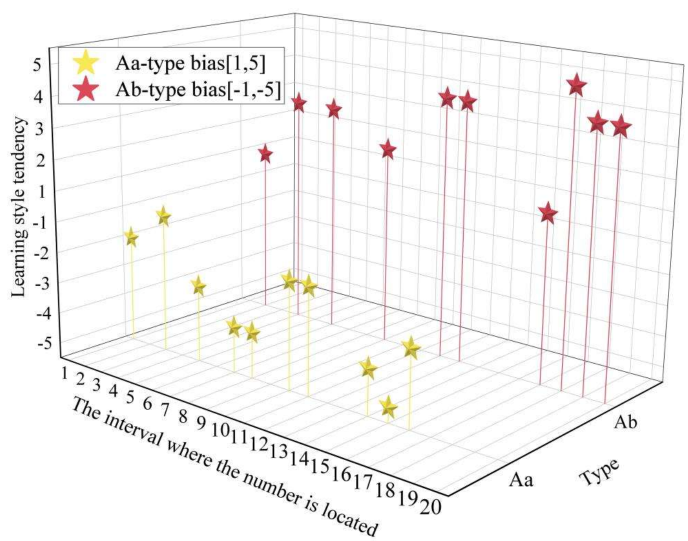


Figure 4: (A) The distribution of students with active and reflective learning styles

In Figure 4, the X coordinate is the numbered interval where the student is located and the Z coordinate is the strength of the two mutually exclusive dimensions under the student's learning style. Where (Aa) active students are in the style intensity interval of [1,5] and the tendency intensity increases as the value increases, and (Ab) reflective students are in the style intensity interval of [-1,-5] and the tendency intensity increases as the value decreases, and the absolute value of the style intensity is taken in the analysis. Each student can have only one learning style tendency under a learning style category, i.e., bias toward active or bias toward reflective.

Among the (A) Active and Reflective learning styles, there were 50 students (50.00%) with (Aa) Active bias with an average strength of 3.00 (3.00). The total number of students with (Ab) reflective tendency is 50 (50.00%) and the mean intensity is 2.50 (-2.50). It can be seen that the percentage of students under both dimensions is equal and (Aa) Active learners have slightly stronger tendencies.

The distribution of students with (B) Perceptual and Intuitive learning styles is shown in Figure 5.

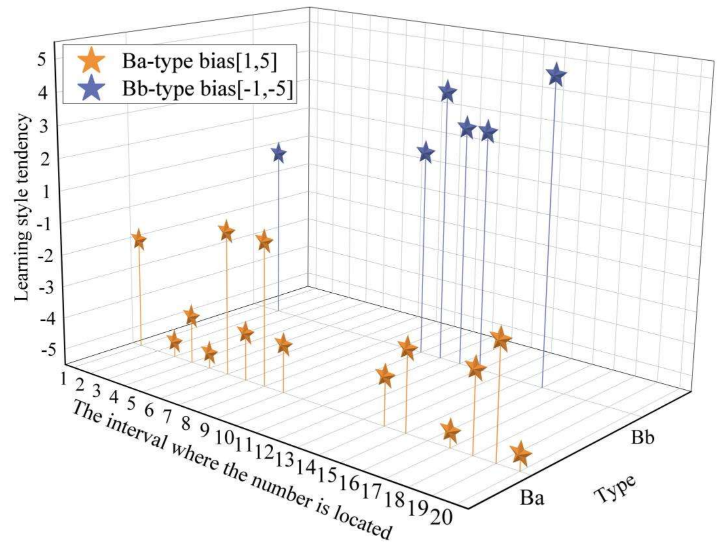


Figure 5: (B) The distribution of students with perceptual and intuitive learning styles

Where (Ba) perceptual students are in the style intensity interval of [1,5] and the tendency intensity increases as the value increases, and (Bb) intuitive students are in the style intensity interval of [-1,-5] and the tendency intensity increases as the value decreases, and the absolute value of the style intensity is taken in the analysis.

Among the (B) perceptual and intuitive learning styles, the total number of students with (Ba) perceptual tendency is 70 (70.00%), which is higher, and the average strength of the style tendency is 2.57 (2.57). The total number of students with (Bb) intuitive tendency is 30 (30.00%) and the mean intensity is 2.50 (-2.50). It can be seen that most of the students under both dimensions are (Ba) perceptual and (Ba) perceptual learners have slightly stronger tendencies.

The distribution of students with (C) visual and verbal learning styles is shown in Figure 6.

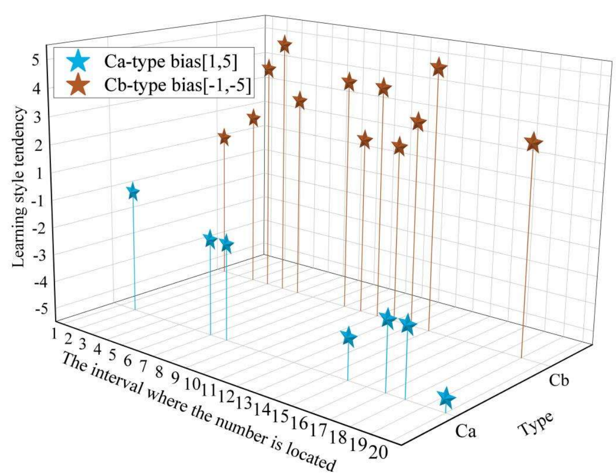


Figure 6: (C) The distribution of students with perceptual and intuitive learning styles

Where (Ca) visual students were in the style intensity interval of [1,5] and the tendency intensity increased as the value increased, and (Cb) verbal students were in the style intensity interval of [-1,-5] and the tendency intensity increased as the value decreased, and the absolute value of the style intensity was taken in the analysis.

Among the (C) visual and verbal learning styles, there were 35 students (35.00%) with (Ca) visual tendency and the average intensity was 3.14 (3.14). The total number of students with (Cb) verbal type tendency is 65 (65.00%)

and the mean intensity is 3.31 (-3.31). It can be seen that there is a small percentage of (Ca) visual type and a high percentage of (Cb) verbal type learners with a slightly stronger tendency under both dimensions.

(D) The distribution of students with sequential and global learning styles is shown in Figure 7.

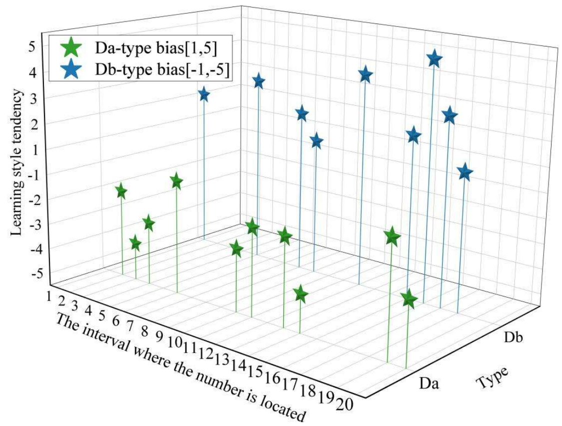


Figure 7: (D) Distribution of students with sequential and global learning styles

Where (Da) Sequential students are in the style intensity interval of [1,5] and the intensity of the tendency increases as the value increases and (Db) Global students are in the style intensity interval of [-1,-5] and the intensity of the tendency increases as the value decreases, and the absolute value of the intensity of the style is taken in the analysis.

Among the (D) Sequential and Global learning styles, there were 55 students (55.00%) with (Da) Sequential tendency and the average intensity was 3.36 (3.36). The total number of students with (Db) global type tendency is 45 (45.00%) and the mean intensity is 2.56 (-2.56). It can be seen that the proportions of students under both dimensions are more or less equal, with a slightly higher percentage of learners with (Da) Sequential type and a significantly stronger tendency than (Db) Global type.

### *IV. B. Application of Personalized Recommendation System*

#### IV. B. 1) Time complexity

The target number of recommended learning resources is set to be 800 video learning resources, and the personalized learning resource recommendation experiments are conducted using (F1) this paper's method, (F2) content-based recommendation method, and (F3) item-based recommendation method, respectively. The best-case time complexity indicates the execution time of the algorithm in the most ideal input case. When the input arrays have been arranged in order from smallest to largest, the algorithm performance can be described in terms of best-case time complexity. Therefore, the time complexity O(n) is used as an indicator to analyze the time complexity of the three methods for recommending 800 video learning resources is shown in Fig. 8 in order to verify the complexity of different algorithms.

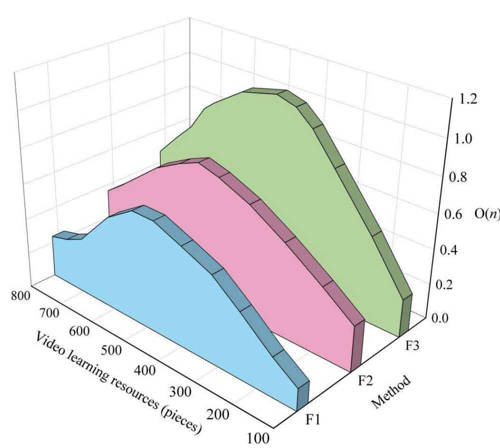


Figure 8: The complexity of different methods

From Fig. 8, it can be seen that the time complexity O(n) of (F1) this paper's method is lower compared to (F2) content-based recommendation method and (F3) item-based recommendation method, and the overall complexity is lower than 0.6. This proves that (F1) this paper's method has a lower complexity for personalized learning resource recommendation and a higher recommendation efficiency.

### IV. B. 2) Resource referral hits

The results of recording the resource recommendation click-through rate of the three methods under different types of resources are shown in Fig. 9.(F1) The recommended click-through rate of this paper's method under different recommended contribution value (RC) conditions is WF1 for text resources, VF1 for video resources, and the same for the remaining two methods.

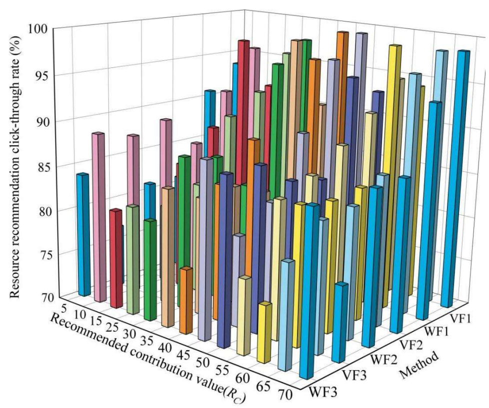


Figure 9: Comparison results of click-through rates for resource recommendations

As can be seen from Figure 9, whether in the recommended text resource click rate or video resource click rate, (F1) the method in this paper are much higher than the remaining two algorithms, not only stable at 90.00% and above and the highest in the recommended contribution value of 70 up to 98.71%. (F2) content-based recommendation method and (F3) item-based recommendation method in different numbers of learning resources under the text resources and video resources recommended click-through rate are relatively low, of which (F2) content-based recommendation method of text resources recommended click-through rate and video resources recommended click-through rate between 80.00%-90.00%, (F3) item-based recommendation method click-through rate for the lowest and fluctuating among the three algorithms, between 75.00%-90.00%.

## V. Conclusion

In this paper, a personalized recommendation method is designed to calculate the similarity between learners' learning styles and learning styles of learning resources, and make the most matching learning resources recommendation. Three recommendation algorithms are used to adapt to the characteristics of learners with different learning styles, and then search for compatible learning resources to establish a personalized recommendation system for Civic Education. According to the specific conditions of the research subjects, learning styles are divided into four types: active and reflective, perceptual and intuitive, visual and verbal, and sequential and global.

The overall time complexity of the Civic and Political Education Personalized Recommendation System is lower than 0.6 in recommending 800 video learning resources, and the click rate of the text resources and video resources remains at 90.00% and above, with a maximum of 98.71%, which is better than that of two similar algorithms in terms of the overall application performance. By combining adaptive algorithms and personalized recommendation, this paper proposes a personalized recommendation system for Civic Education that takes into account both stability and practicality.

## References

[1] Hu, W. (2024). Research on the Ideological and Political Education in the Curriculum of Human Resource Management in China. Open Journal of Applied Sciences, 14(5), 1295-1304.

[2] Sun, M., & Wang, S. (2020, June). The practical study on the teaching reform of “Ideological and Political Education” in Western Economics Courses. In 2020 5th International Conference on Smart Grid and Electrical Automation (ICSGEA) (pp. 538-541). IEEE.

[3] Yuan, X. (2020). On the means of ideological and political education in colleges and universities under the new media environment. International Journal of New Developments in Education, 2(7).

[4] Feng, L., & Dong, Y. (2022). Teaching quality analysis of college ideological and political education based on deep learning. Journal of Interconnection Networks, 22(Supp05), 2147006.

[5] Zong, W., Zhai, H., Chen, H., & Pan, H. (2020, January). Exploration and practice of Ideological and political education in mechanical design course. In 2019 3rd International Conference on Education, Economics and Management Research (ICEEMR 2019) (pp. 180-182). Atlantis Press.

[6] Liu, Q., Tang, Z., & Zhang, S. (2024, September). Ideological and Political Education in the Mobile Internet Era: A Survey. In 2024 4th International Conference on Educational Technology (ICET) (pp. 325-329). IEEE.

[7] Xiu-zheng, T. (2018). Construction and optimization of ideological and political education for college students based on mobile network platform. US-China Education Review B, 8(4), 10-17265.

[8] Huang, L. (2024). Research on Mixed Education Teaching Reform in the Era of Internet plus. Journal of Theory and Practice of Social Science, 4(02), 1-6.

[9] Delgado, H. O. K., de Azevedo Fay, A., Sebastiany, M. J., & Silva, A. D. C. (2020). Artificial intelligence adaptive learning tools: the teaching of English in focus. BELT-Brazilian English Language Teaching Journal, 11(2), e38749-e38749.

[10] Smaili, E. M., Khoudda, C., Sraidi, S., & Charaf, M. E. H. (2020, December). An optimized method for adaptive learning based on PSO Algorithm. In 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS) (pp. 1-5). IEEE.

[11] Hssina, B., & Erritali, M. (2019). A personalized pedagogical objectives based on a genetic algorithm in an adaptive learning system. Procedia Computer Science, 151, 1152-1157.

[12] Chang, Z., & Liu, K. (2023). Construction of a personalised online learning resource recommendation model based on self-adaptation. International Journal of Knowledge-Based Development, 13(2-4), 394-410.

[13] Dai, J., Gu, X., & Zhu, J. (2023). Personalized recommendation in the adaptive learning system: The role of adaptive testing technology. Journal of Educational Computing Research, 61(3), 523-545.

[14] Kem, D. (2022). Personalised and adaptive learning: Emerging learning platforms in the era of digital and smart learning. International Journal of Social Science and Human Research, 5(2), 385-391.

[15] Sabeima, M., Lamolle, M., & Nanne, M. F. (2022). Towards personalized adaptive learning in e-learning recommender systems. International Journal of Advanced Computer Science and Applications, 13(8), 14-20.

[16] Liu, C., & Tuntiwongwanich, S. (2024). Enhancing Personalized Learning in Online Education: The Impact of Adaptive Learning Systems and Recommendation Technologies. Eurasian Journal of Educational Research (EJER), (112).

[17] Lalitha, T. B., & Sreeja, P. S. (2020). Personalised self-directed learning recommendation system. Procedia Computer Science, 171, 583-592.

[18] Apoki, U. C., Hussein, A. M. A., Al-Chalabi, H. K. M., Badica, C., & Mocanu, M. L. (2022). The role of pedagogical agents in personalised adaptive learning: A review. Sustainability, 14(11), 6442.

[19] Taylor, D. L., Yeung, M., & Bashet, A. Z. (2021). Personalized and adaptive learning. Innovative learning environments in STEM higher education: Opportunities, Challenges, and Looking Forward, 17-34.