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Article

Algorithmic Research on Integration and Optimization of Civic and Political Teaching Resources of University English Courses under Digital Transformation

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Abstract: This paper utilizes and continuously improves the teaching resources of Civics and Politics in university English courses from two aspects. On the one hand, K-means clustering algorithm, distance function optimization method and SimHash method are introduced to effectively classify the existing teaching resources and extract key features to provide data support for dynamic retrieval. On the other hand, through ontology construction, persistence algorithm and teaching resources optimization effect evaluation model, the unavailable teaching resources are uploaded to optimize the resource library and quantify the optimization effect to improve the utilization efficiency of resources. The redundancy ratio of integrated information for resource classification and retrieval is less than 2%. The classification accuracy rate and classification effect F1 value are both greater than 90% and 0.9. The resource search rate is above 91%.

Keywords: curriculum civics; K-means clustering; distance function optimization; SimHash; teaching resources integration

1. Introduction

With the continuous iterative development of modern information technology, digital technology, with its advantages of efficiency, convenience and intelligence, has been deeply integrated into various fields of society, including education. Combining digital technology and Civic Education has become an inevitable trend in modern education. Digital ideology and politics is an ideological and political education system based on big data, cloud computing, 5G technology, artificial intelligence, virtual reality, augmented reality and other digital technologies, using data elements, integrating and classifying ideological and political resources, comprehensive analysis, aiming to improve the quality and efficiency of ideological and political education, and digitizing and integrating the whole process and multi-dimensions [1]. Digital ideological politics has the following three characteristics: digital technology is the foundation, quality and efficiency is the purpose, and the whole process of deep integration is the key. The rapid change of digital technology and the popularity of curriculum ideology and politics have laid a solid technical foundation for the rapid development of “digital ideology and politics” and pointed out the correct value direction.

As an important part of higher education, university English has the feasibility, necessity and urgency to carry out digital ideological politics. The in-depth integration of digital technology and curriculum civic politics is not only conducive to improving students' comprehensive English language ability, but more importantly, it can deepen students' ideological and political literacy and realize the fundamental goal of higher education to cultivate morality and nurture people [2]. In the context of digital transformation, the value of ideology and politics contained in the university English course is becoming more and more prominent. The course can not only profoundly influence students' ideology, but also effectively cultivate their correct values and worldview. With the help of digital tools, English teaching has gone beyond the mere teaching of language skills to become an important platform for leading students' ideology. Students are exposed to richer cross-cultural resources and global perspectives, thus stimulating deeper reflection on social, cultural and national values. This kind of ideological education is skillfully integrated into language learning, which is not only reflected in the teaching content, but also invisibly guides students' thoughts and enhances their sense of social responsibility and critical thinking [3]. Driven by digital transformation, the penetration of ideological and political education is effectively deepened by enhancing teaching interaction and student participation [4]. The support of digital technology has transformed the English course from a single language teaching to a multifunctional platform integrating knowledge transfer and ideological education. Digital tools help teachers accurately control students' participation and learning status, implement personalized education, and thus optimize the effect of Civic and Political Education [5-6].

In addition, digital technology has injected new vitality into English language teaching by providing diversified teaching tools and resources to facilitate language learning. With the help of digital platforms, English courses are able to demonstrate China's social progress and international layout by combining actual cases in multiple fields around the world, which not only exercises students' language skills, but also enables them to deeply comprehend the country's development, cultural background and socialist core values in the learning process [7-8]. At the same time, digital tools help teachers accurately grasp students' learning dynamics, flexibly adjust the teaching content, and realize the perfect combination of Civics elements and language teaching, so as to enhance students' sense of social responsibility, ethical and moral concepts, and global awareness [9-10].

Intelligent optimization algorithms, as an emerging optimization technology, can achieve optimal solutions under multi-objective and multi-constraint conditions, and are widely used in the solution of complex optimization problems, such as processing scheduling problem, elevator operation problem, power scheduling problem, transportation problem, traveler's problem, knapsack problem, crating problem, resource allocation problem, and class scheduling problem, etc [11]. The goal of intelligent optimization algorithms is to solve optimization problems, one is the function optimization problem of solving a function in which the value of the independent variable that minimizes the value of the function is taken [12]. The second is the combinatorial optimization problem of finding the optimal solution to minimize the value of the objective function inside a solution space [13]. The principle of intelligent optimization algorithms is simply to consider a series of different input variables at a point in time, and search for the variables according to the objective function set by the user, in the expectation of making the system reach the optimal state.

In the traditional teaching procedure, there are problems of resource waste and underutilization. Intelligent optimization algorithm can realize dynamic allocation and adjustment of teaching resources through real-time tracking and analysis of students' learning, learning performance and resource demand. Moreover, the intelligent optimization algorithm can realize more reasonable teacher allocation according to students' needs and teachers' specialties and experiences. For example, more appropriate teaching tasks can be assigned to teachers according to the curriculum needs of different majors to ensure teaching quality. In addition, intelligent optimization algorithms can provide personalized learning solutions and resource recommendations based on students' learning situations and interests. This helps to meet the learning needs of different students and improve learning motivation and effectiveness.

Evolutionary computation is an algorithm that simulates the group behavior of organisms in nature, and it is also the most applied algorithm in the research field of optimization problems [14]. According to the theory of biological evolution, organisms in the process of their own evolution, constantly undergo the selection of superiority and inferiority, and the good individuals are retained, which is the process of evolution [15]. Jaimes et al [16] introduced the Chebyshev preference information in the non-dominated sequential genetic algorithm on the construction of multi-objective spatial ballistic optimal design model solution. Trojovský [17] proposed the preschool optimization algorithm based on human thinking, which can provide an effective solution for the objective function, showing excellent optimization effect in 22 optimization problems and 4 engineering design problems. Ye et al [18] constructed a cloud workflow scheduling model based on the cost required to complete the workflow, the maximum completion time, and the average completion time, and solved the model through the improved KnEA algorithm.

The research hotspots of optimization algorithms by foreign scholars include the improvement of algorithms and their applications in several fields, and the same fruitful results have been achieved in the field of education [19]. Xu [20] provided a systematic overview of the application of optimization algorithms in higher education management and personalized teaching, and the algorithms have achieved significant results in improving students' classroom learning outcomes, participation, satisfaction and efficiency, and have great application potential. Wang et al [21] established an immersive physical education teaching environment equipped with Kinect technology and VR support, where support vector machines and particle swarm optimization algorithms collaborated to generate interactive physical education content, and classify and evaluate students' physical education performance, which stimulated students' interest in physical education learning and improved teaching quality.

Teaching quality assessment is an important part of the daily management process, is a complex and abstract nonlinear problem, affected by a variety of factors, the change rule is more complex [22]. Since the traditional quality assessment model can no longer meet the requirements of the current complex quality assessment work, the use of intelligent algorithms to effectively improve the efficiency and accuracy of quality assessment has become a current research hotspot [23]. Weimin [24] in order to improve the assessment effect of classroom education, constructed a classroom education effect assessment model based on intelligent optimization algorithms, using logarithmic spiral curves to simulate the path of moths moving towards the flame moving paths, using the diversity of moth populations to make them find better classroom effectiveness assessment strategies in the search space. Popescu [25] proposed an enhanced genetic algorithm for the problem of test generation for educational assessment, which is able to quickly provide high-quality solutions that match the defined fitness directions in large-scale test generation tasks. Thaher et al [26], in order to increase the prediction accuracy of students' academic performance, they proposed a student performance prediction model based on whale optimization algorithm and combined it with sine-cosine algorithm and logical chaos mapping to improve the overall performance of the model and outperform other methods in testing. Ma et al [27] constructed a teaching quality evaluation system using quantum particle swarm optimization algorithm, which is loaded with a number of real-world application functions and improves the system security performance through user name and password, and the system provides more accurate and scientific assessment results than in the teaching assessment test.

In addition, the research of various experts and scholars on the fields related to the allocation of teachers and teaching resources is also advancing in exploration, and their focus areas are concentrated on the rationality of the exploration of the allocation of educational resources [28]. Ying et al [29] used a fuzzy particle swarm optimization algorithm to find the optimal allocation scheme of educational resources, which ranges from the determination of the objective function and constraints to fuzzy processing, and then generates multiple resource allocation schemes, and the optimal allocation scheme can be obtained through the continuously updating until the particle position reaches the optimal solution, the optimal allocation scheme can be obtained. Xiao [30] proposed an improved ant colony optimization algorithm and combined it with the English teaching resource recommendation model, the optimization algorithm provides a fast and comprehensive resource integration scheme for the recommendation model, has good data training quality, and enhances the model's performance of the English language resource recommendation. Li, H et al [31] used a multi-objective approach in the learning resource recommendation model embedded in a multi-objective optimization algorithm, which provides diverse and novel recommendation strategies for the model through learning clustering, optimization goal setting, individual representation, and genetic operations, and the results show that the multi-objective optimization algorithm improves the performance of the recommendation model. Li, W et al [32] applied particle swarm algorithm as a teaching resource optimization model to higher education.In resource allocation test, particle swarm algorithm provides more efficient strategy for resource allocation to educational institutions and reduces unnecessary waste of resources. Zhang [33] pointed out that faculty is the core force to achieve optimal information transfer and teaching quality.The study used non-dominated sorting genetic algorithm to optimize university faculty structure was optimized to enhance the educational level and academic achievement of universities. Gupta et al [34] solved the university faculty planning problem through genetic algorithm by specifying the number of professors, associate professors, assistant professors, visiting/adjunct faculty, and non-teaching staff and describing the budgetary goals for each academic department to support the academic staff in different departments in the long term planning process. Fieldsend [35] divided the university faculty teaching allocation problem into seven optimization objectives and used an enhanced non-dominated sorting genetic algorithm for objective function optimization solving to provide a reasonable teaching allocation strategy by taking into account the workload allocation balance and other objectives.

In this paper, we use K-means clustering algorithm and distance function optimization method to classify the original resources of university English teaching into two categories, image and text, and reduce the negative influence of noisy data on clustering. The feature vectors of resources in each category are extracted from the original data by SimHash method, which efficiently accomplishes data reduction and semantic preservation and improves the dynamic indexing efficiency. For resources that do not exist in the repository, the administrator builds an ontology that connects the knowledge points and concepts of related subjects, and clarifies the hierarchical relationship between the ontology resources. Afterwards, the ontology data is stored into the resource base through the persistence algorithm to optimize the resource base. A simulation model of teaching resource optimization is constructed to measure and evaluate the optimization effect from multiple index dimensions, and adjustments are continuously made according to the evaluation results.

2. Construction and Optimization of Civic and Political Teaching Resource Base for University English Courses

2.1. Hierarchical dynamic indexing method for teaching resources in mass storage systems

2.1.1. Clustering of teaching resources

Image resources are usually stored in the form of pixel matrices, whose semantic information needs to be parsed by visual feature extraction and deep learning models, while text resources are stored in the form of character sequences, which can be directly accessed by natural language processing techniques. By clustering resources into image and text classes, specialized indexing structures and retrieval algorithms can be designed for different types of resources, thus improving the efficiency and accuracy of indexing. To this end, this paper clusters the resources for teaching Civics and Politics in university English courses into image and text classes by using the K-meanss clustering algorithm. In order to improve the accuracy of clustering, representative feature words are extracted from the teaching resources, and the categories with larger attribute values are used as the core of feature words to better portray the essential attributes of the resources. Since the K-meanss clustering algorithm is more sensitive to the initial clustering center and noisy data, it may lead to unstable clustering results. For this reason, this paper dynamically adjusts the distance calculation in the clustering process by introducing a distance function optimization method to reduce the impact of noisy data on the clustering results, so as to improve the robustness of the algorithm and optimize the clustering effect. This method is not only able to effectively distinguish between image-type and text-type resources, but also to lay a more reliable data classification foundation for the subsequent hierarchical dynamic indexing. Set the clustering function $\Re$ for clustering teaching resources in the K-meanss clustering algorithm, and its expression is:

$$\Re = \sqrt{\sum_{n=1}^{N} (Q_{i,n} - Q_{i-1,n})^{\alpha}} \tag{1}$$

Where: $Q_{i,n}$ denotes the n th attribute of term i ; $Q_{i-1,n}$ denotes the n th attribute of term $i-1$; α denotes the moderating coefficient that can reduce the effect of outliers; and N denotes the maximum value of n , i.e., the upper limit of summation. $Q_{i,n}$ is adjacent to $Q_{i-1,n}$. Using equation (1), the clustering of teaching resources can be accomplished.

2.1.2. SimHash-based feature extraction for data indexing

Due to the diversity and complexity of the Civics teaching resources of university English courses, direct indexing of the raw data will lead to inefficiency and is difficult to meet the demand for accurate retrieval, so it is necessary to extract data indexing features. By extracting data indexing features, representative key information can be mined from massive resources, such as keywords and topic distribution of text resources, and visual features and color histograms of image resources. These features can effectively reduce the dimensionality of data and retain the essential semantic information of resources.

Constructing an index based on the extracted features not only significantly improves the retrieval efficiency, but also supports a multi-level dynamic index structure, so that the system can quickly locate the target resources, adapt to the dynamic updating of the resources, and satisfy the diversified retrieval needs of the users, thus providing a technical guarantee for the efficient management and retrieval of the vast amount of teaching resources of Civics and Politics of the university English course.

The core ability of SimHash is to retain the similarity information while compressing data, and realize the fast nearest-neighbor search of massive data through efficient Hamming distance computation, which is an ideal choice for big data indexing.SimHash can map high-dimensional feature vectors to low-dimensional hash values, which can significantly reduce the storage and computational complexity while retaining the semantic similarity of data. For teaching resources, SimHash can quickly generate a unique fingerprint of the resource, and even if there are minor differences in the content of the resource, its hash value can still maintain a high degree of similarity, which makes it perform well in detecting duplicate and similar resources. In addition, the computation process of SimHash is simple and efficient, which is suitable for processing large-scale data and can provide a stable and scalable feature representation basis for hierarchical dynamic indexing. Before the hierarchical dynamic indexing of teaching resources in mass storage systems, it is necessary to complete the extraction of feature vectors for teaching resources and store the vectors in the indexing database in binary form.

In this paper, we use SimHash method to extract teaching resource vectors. First, the inverse document frequency J of teaching resource keywords is calculated with the expression:

$$\mathrm{J} = \lg\left[M / (E + c)\right] \tag{2}$$

Where: M is the full number of words in the teaching resource database; c is a constant. In order to avoid the case where the denominator is 0.0, the inverse document frequency of teaching resource keywords needs to be calculated so as to obtain the frequency weight of teaching resource keywords. Its calculation formula is:

$$\omega = \chi \cdot \mathrm{J} \tag{3}$$

Where: χ is the average contribution variable of teaching resource keywords. Then, new words are added to the teaching resource keywords to get the weights ω' of the teaching resource keywords, which is calculated by the formula:

$$\omega' = \frac{\omega \cdot K \cdot L}{\sqrt{\sum_{n=1}^{N} (\omega_N \cdot K)^{-1} \cdot L}} \tag{4}$$

Where: K is the frequency of occurrence of new words; L is the length of added new words. Through the lexical weights to the set of weight vectors, the values in the set are merged and dimensionality reduced to obtain the teaching resources indexing feature vector.

2.2. Resource retrieval system implementation

2.2.1. Basic concepts and terminology

In an ontology construction exercise, if there is no ontology to reuse, teaching practitioners need to build their own ontology. After determining the domain scope of the ontology, it is necessary to analyze all the knowledge points and concepts in the subject domain for the construction of the precise ontology. Ontology is the foundation of semantic retrieval and also the key factor of whether semantic retrieval is efficient or not, so it is very necessary to analyze the knowledge points and concepts in the subject domain thoroughly.

2.2.2. Hierarchy of basic concepts

When using the ontology to calculate the semantic similarity, the semantic distance between two concepts in the ontology tree and the attribute similarity of the two concepts are actually utilized, and the semantic distance relies on the actual distance between the two concepts in the ontology tree, i.e., their shortest path in the ontology tree. Therefore, the hierarchical relationship between concepts in the ontology is particularly important, and analyzing the hierarchical relationship between concepts and knowledge points in the subject is the key to constructing a qualified ontology.

2.2.3. Persistence algorithms

After building the data table keyword, you can persist the ontology to the database. The jena reasoning function and jena's query function need to be used in the persistence process. In the keyword into the database, you need to fill out all the fields, of which Depth, Width, Weight three fields need to be calculated to get, so the main introduction in the persistence process of how to get the three fields, the other fields in the persistence of the ontology file in the specific contents of the direct reading, so do not introduce.

Depth: denotes the depth of the concept in the ontology tree, let the depth of the root node Root of the ontology tree is 1.0, and the depth of any other node is the depth of its parent node plus one. If the depth of concept C is represented by the function $\mathrm{Dep}(C)$, the depth calculation formula is Equation (5), where $\mathrm{Parent}(C)$ represents the parent node of concept C.

$$\mathrm{Dep}(C)=\begin{cases}1.0, & C=\mathrm{Root}\\ \mathrm{Dep}(\mathrm{Parent}(C))+1.0, & C\neq \mathrm{Root}\end{cases} \tag{5}$$

When the system reads in an ontology file, it first reads in the root node of the ontology file and assigns its Depth attribute to 1.0 when it dumps the node as a keyword, and then the system reads in its child nodes and assigns the Depth attribute of the child nodes to 2.0, i.e., the value of the Depth attribute of the root node is increased by 1.0, and so on, so that the Depth attribute values of all the concepts can be added. Depth attribute value.

Width: indicates the width of the concept, and its value is the number of direct child nodes the concept has. When getting the lower nodes of a concept into a childList, the number of elements in the childList is the width of the concept, and $\mathrm{Wid}(C)$ is used to represent the width of concept C.

Weight: the weight of the concept, use $\mathrm{Weight}(C)$ to represent the weight of the concept C, $\mathrm{Parent}(C)$ is the parent node of the concept C, the weight of the concept C is calculated as follows:

$$Weight=\begin{cases}\dfrac{1}{Wid(C)}, C=Root\\ \dfrac{1}{2}\times\dfrac{1}{Wid(C)}\times Weight\left(Parent(C)\right), C\neq Root\end{cases} \tag{6}$$

When the system persists all the nodes in the ontology to the database, the system uniformly updates all the data in the KEYWORD table, and calculates the weights of all the concepts by using formula (6). In this paper, the weights of all edges induced from concept C are the weights of concept C, so when calculating the semantic distance between concepts, it is enough to use the weights of concepts directly.

2.3. Model construction and analysis of resource optimization effect assessment

2.3.1. Simulation Model Design for Teaching Resource Optimization

In order to scientifically assess the effect of optimizing the teaching resources of Civics and Politics in college English courses under the background of informationization, the paper constructs a simulation model of teaching resources optimization based on multi-indicator evaluation. The model takes the utilization rate of teaching resources (U), student satisfaction (S), learning effect enhancement rate (E) and resource allocation fairness (F) as the core indicators, and quantitatively analyzes the optimization effect by combining the performance of these indicators.

The model formula is as follows:

$$M=w_1U+w_2S+w_3E+w_4F \tag{7}$$

Where M is the comprehensive score of optimization effect; w_1,w_2,w_3,w_4 are the weights of each index respectively, which satisfy $\sum w_i=1.0$. The model can provide a quantitative basis for the effects of different optimization schemes and support the decision-making of teaching resource management and allocation.

2.3.2. Numerical simulation parameterization

In order to verify the validity of the simulation model, the paper went through the changes before and after the optimization of the teaching resources of Civics and Politics in college English courses and designed the following formula for calculating the value of each index:

1) Utilization of Teaching Resources (U)

$$U = \frac{R_u}{R_t} \times 100\% \tag{8}$$

Where R_u is the number of teaching resources actually used and R_t is the total number of resources.

2) Student Satisfaction (S)

$$S = \frac{\sum_{i=1}^{n} s_i}{n} \tag{9}$$

Where s_i is the satisfaction rating of the i th student, n is the total number of students, and the rating range is 1~10.

3) Learning Effect Improvement Rate

$$E = \frac{P_{\text{After}} - P_{\text{Before}}}{P_{\text{Before}}} \times 100\% \tag{10}$$

where P_{Before} and P_{After} are the average scores of the test before and after resource optimization, respectively.

4) Resource allocation fairness (F)

$$F = 1 - \frac{\sum_{i=1}^{m} |x_i - \overline{x}|}{m\overline{x}} \tag{11}$$

where x_i is the amount of resources allocated to the i th district, $\overline{x}$ is the average value of resource allocation, and m is the number of districts.

2.3.3. Technical processes for assessment analysis

The paper divides the evaluation of resource optimization effect into the following four technical phases: data collection phase: obtain resource usage data, student satisfaction survey results and test score change data through the teaching platform to ensure the comprehensiveness and accuracy of the data; model parameter setting phase: set the weights and initial data according to the actual situation, and correct the weights with the expert's suggestions; simulation calculation phase: calculate the values of indicators before and after optimization with simulation model, and compare the comprehensive scores; results analysis phase: visualize and analyze the model output results, and put forward improvements in combination with teaching practice. Simulation calculation stage: use the simulation model to calculate the values of each index before and after optimization, compare the comprehensive scores, write a program to realize the model solution through MATLAB, and output the optimization effect scores; Results analysis stage: visualize and analyze the results of the model output, put forward the improvement suggestions in combination with the teaching practice, and verify the consistency between the model prediction and the actual effect.

3. Study on the effectiveness of resource integration and optimization

3.1. Selection of Teaching Resources for Civics in the Curriculum

When analyzing the application effect of the teaching resource integration method (K-means + distance function optimization + SimHash) of the Civics mass storage system for university English courses designed in this paper, a comparison test was launched. Among them, density-based classification algorithm (DBSCAN), grid classification algorithm (STING), and sampling collection algorithm (Clara) are chosen as comparison methods. For the test data, this paper takes the corpus built by a university English course Civics teaching platform itself as the source of test data. The corpus contains about 4,500 image and text resources of various types of English course Civics, and is characterized by uneven distribution. In terms of the classification of specific course Civics resources, it contains seven categories: daily English teaching resources (A1), leisure English teaching resources (A2), vocational English teaching resources (A3), current affairs English teaching resources (A4), English writing teaching resources (A5), cross-cultural communication English teaching resources (A6), and English newspapers and magazines reading resources (A7). In this paper, 70% of these images and texts are used as the training set, i.e., 3150 resources are used as the training set. The remaining 30% is used as the test set. Figure 1 shows the selection of resources for teaching Civics in various types of courses. There are 721, 285, 463, 338, 543, 445, and 355 resources of course Civics in categories A1-A7 contained in the training set, and 210, 174, 201, 153, 302, 195, and 105 resources of course Civics in categories A1-A7 contained in the test set.

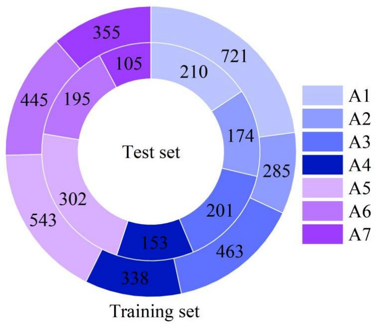

Figure 1. The selection of various teaching resources

3.2. Comparison of different resource integration and optimization methods

3.2.1. Comparison of redundancy ratios of integrated information

After preparing the test data according to Fig. 1, the four methods were used to conduct classification tests and examine the resource classification effect and integration optimization effect respectively. Figure 2 compares the information redundancy ratios (taking the average ratio between the training set and the test set) of the 4 methods for integrating teaching resources. The integration information redundancy ratios of this paper's method are 1.73%, 1.65%, 1.58%, 1.02%, 1.26%, 1.51%, 1.22%, respectively, which are less than 2.00% when classifying the 7 types of teaching resources for Civics and Politics of the English course into 2 categories, namely, image and text. In contrast, the redundancy ratio of integrated information for the DBSCAN method ranges from 16.06% to 22.31%, the STING method ranges from 21.34% to 28.37%, and the Clara method ranges from 19.48% to 25.11%. There is a nearly 10-fold difference in the integrated information redundancy ratio between the methods in this paper and the comparison methods.

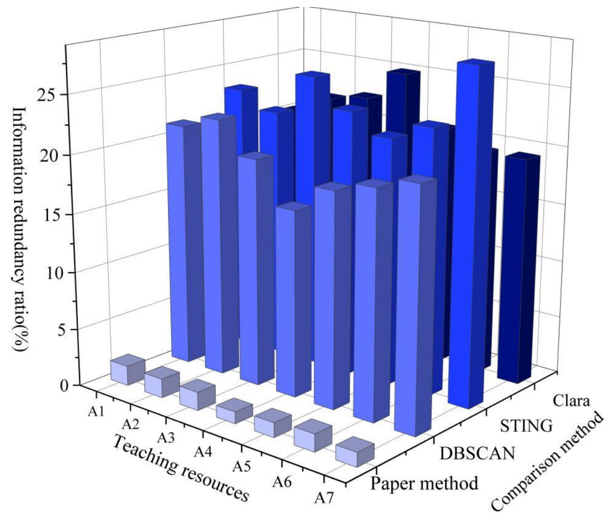

Figure 2. Information redundancy ratio of resource integration for 4 methods

3.2.2. Comparison of classification accuracy

Figure 3 shows the comparison of resource classification accuracy of the four methods. The classification accuracy of this paper's method ranges from [90.95, 94.72]%, and the difference between the highest and the lowest accuracy is 3.77%, which is not more than 4%. The classification accuracy of the three comparison methods all fluctuates greatly between 60% and 90%, and the highest accuracy is only 89.43%, which is smaller than the lowest value of the classification accuracy of this paper's method. The classification accuracy and stability of this paper's method are better.

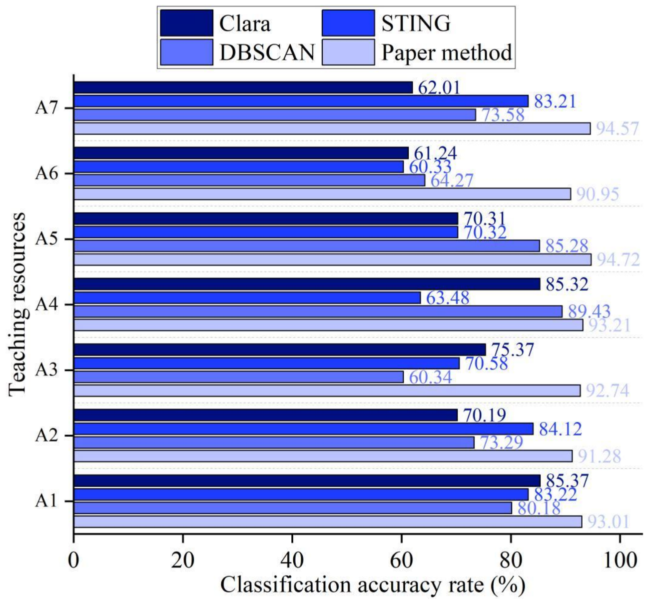

Figure 3. The accuracy rates of resource classification for the four methods

3.2.3. Comparison of F1 values for classification effects

Figure 4 shows the comparison of the F1 value of the classification effect of different methods. The F1 values of the classification effect of the seven types of Civic and Political Teaching Resources for College English Course of this paper's method are 0.93, 0.92, 0.94, 0.96, 0.92, 0.91, 0.95 respectively, which are above 0.90 and close to 1.00. The classification effect of the different resources is relatively average and stable. Compared with other methods, the resource classification effect of this paper's method is more prominent.

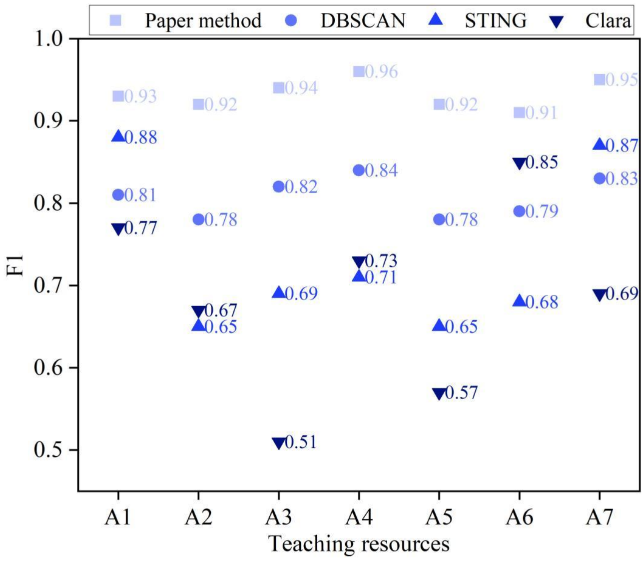

Figure 4. Comparison of F1 values for classification effects of different methods

In the comparison of integrated information redundancy ratio, classification accuracy and classification effect, the performance of this paper's method is more excellent. The reason is that, in the classification process, this paper's method combines the K-means clustering method and the distance function optimization method to reduce the noise of the original resource data, thus reducing the redundant information in the classification process, resulting in a higher level of classification and better stability.

3.2.4. Comparison of resource identification rates

Figure 5 shows the results of the resource identification rate under the classification and integration of the 4 types of methods. As can be seen from Fig. 5, all four methods show a decreasing trend of checking rate with the increase of data volume. However, it is clear that the search rate of this paper's method is always maintained at a high level (more than 91%), and the fluctuation is small (fluctuation is about 1%). In contrast, the detection rates of the three compared methods do not exceed 90%. Thanks to the feature extraction of the SimHash method, the dynamic retrieval rate of this method is higher.

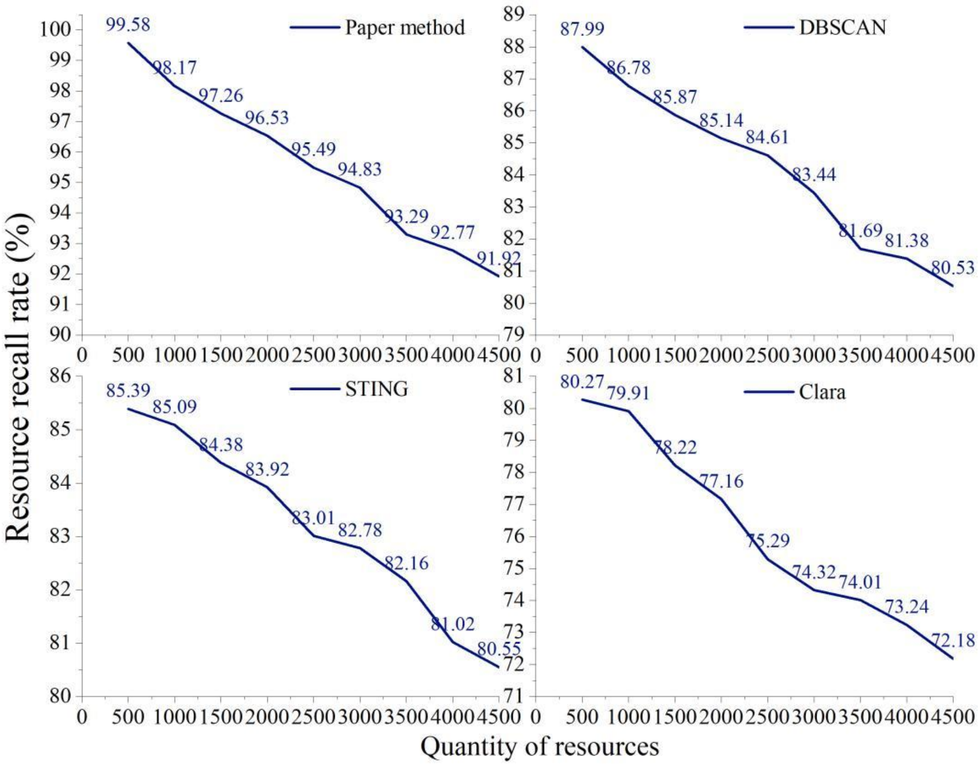

Figure 5. The resource recall rates of the four types of methods

3.3. Assessment of the effectiveness of resource optimization

3.3.1. Ease of use analysis

The optimized massive retrieval system of teaching resources for university English courses was applied to the freshman and sophomore business English majors in a university to assist 250 students in retrieving major-related resources. Afterwards, through questionnaire surveys and data analysis, students' evaluations of the system's ease of use were collected, and the evaluation model of resource optimization effect was used to quantify the system's effect on improving the quality of students' learning of English courses in Civics and Politics.

Table 1 shows the results of students' evaluation of the system's ease of use. According to the results of the questionnaire survey, the maximum values of 250 students' ratings for the four dimensions of the system's retrieval of resources were 4.93, 5.00, 4.98, and 5.00, which were close to the full score of five. And the minimum and mean scores were above 4.50. This indicates that students are more satisfied with the continuously optimized resource system and consider it to have high application value.

Table 1. Students' evaluation of the system's usability

	Platform functions	Information acquisition	Content presentation	Retrieval tool
N	250	250	250	250
Maximum value	4.93	5.00	4.98	5.00
Minimum value	4.59	4.91	4.72	4.68
Average value	4.72	4.94	4.83	4.77
Standard deviation	0.10	0.27	0.31	0.24

3.3.2. Analysis of upgrading effects

Using the resource optimization effect assessment model, combined with the collected data, the resource retrieval system is quantitatively analyzed in terms of four aspects: teaching resource utilization, student satisfaction, learning effect enhancement rate, and resource allocation fairness, for the enhancement effect on learning quality. Table 2 shows the results of the assessment of learning quality improvement effect. The average scores of 4.82, 4.99, 4.80, and 4.72 in the assessment model's calculation of the enhancement effect of the four indicators are at a high level. It indicates that the use of clustering + noise reduction + feature extraction + continuous optimization can optimize the quality of the resource retrieval system as a whole, so as to provide students with more and better teaching resources for Civics and Politics of the university English course and to improve the quality of student learning.

Table 2. Evaluation results of the effect of learning quality improvement

Indicator	N	Minimum value	Maximum value	Average value	Standard deviation	Contrast
Utilization rate of teaching resources	250	4.77	4.99	4.82	0.21	0.15
Student satisfaction	250	4.98	5.00	4.99	0.34	0.20
Learning effect improvement rate	250	4.73	5.00	4.80	0.19	0.06
Fairness in resource allocation	250	4.61	4.98	4.72	0.15	0.12

4. Conclusion

This paper integrates clustering, feature extraction, persistent uploading, and effect evaluation methods to integrate the teaching resources of Civics and Politics in college English courses, and continuously optimizes them. In the comparison of the four types of methods, the integration information redundancy ratio, classification accuracy rate, classification effect F1 value, and resource checking rate of this paper's method are all at the optimal level. The redundancy ratio of integrated information is below 2%, the classification accuracy rate is stable above 90%, the F1 value is always greater than 0.9, and the resource search rate is higher than 91%. Students made a high evaluation of the ease of use of the retrieval resource system, with the four dimensions scoring close to 5 points. Through the evaluation model, it is judged that the optimization of the system in the 4 indicators of teaching resource utilization, student satisfaction, learning effect enhancement rate, and resource allocation fairness can effectively improve the quality of student learning.

References

1. Li, M. (2024). Intelligent Platform of Ideological and Political Education Resources under Digital Education Environment [J]. Adv. Educ. Technol. Psychol, 8(1).
2. Fu, Y. (2025). Research on Integrating Ideological and Political Education into College English Course Under the Background of Teaching Digital Transformation. The Educational Review, USA, 9(3).
3. Luo, H. (2025, June). The Development and Construction of College English Digital Textbooks from the Perspective of “Great Ideological and Political Course”. In 2025 4th International Conference on Humanities, Wisdom Education and Service Management (HWESM 2025) (pp. 108-114). Atlantis Press.
4. Joseph, O. B., Onwuzulike, O. C., & Shitu, K. (2024). Digital transformation in education: Strategies for effective implementation. World Journal of Advanced Research and Reviews, 23(2), 2785-2799.
5. Sych, T. V., Khrykov, Y. M., & Ptakhina, O. M. (2021). Digital transformation as the main condition for the

development of modern higher education. Educational Technology Quarterly, 2021(2), 293-309.
6. Useche, A. C., Galvis, Á. H., Díaz-Barriga Arceo, F., Patiño Rivera, A. E., & Muñoz-Reyes, C. (2022). Reflexive pedagogy at the heart of educational digital transformation in Latin American higher education institutions. International journal of educational technology in higher education, 19(1), 62.
7. Jia, W., Wenying, X., Yaling, Z., & Chunyan, L. (2024). How Students Use Hybrid College English Teaching Platforms: A Systematic Review in China. Social Sciences Review and Humanities, 3(2), 38-49.
8. Abdishukurova, S. (2025). THE ROLE OF TECHNOLOGY IN LANGUAGE LEARNING: ENHANCING ENGLISH PROFICIENCY THROUGH DIGITAL TOOLS AND PLATFORMS. Global Science Review, 2(1), 131-139.
9. García-Martínez, J. A., Rosa-Napal, F. C., Romero-Tabeayo, I., López-Calvo, S., & Fuentes-Abeledo, E. J. (2020). Digital tools and personal learning environments: An analysis in higher education. Sustainability, 12(19), 8180.
10. Liton, H. A. (2022). Social media as assistive learning tools in digital learning dynamics: An experiential learning reflection. Managing Technology & Innovation in Teaching and Learning, 86-94.
11. Xu, M., Cao, L., Lu, D., Hu, Z., & Yue, Y. (2023). Application of swarm intelligence optimization algorithms in image processing: A comprehensive review of analysis, synthesis, and optimization. Biomimetics, 8(2), 235.
12. Liao, T., Stützle, T., de Oca, M. A. M., & Dorigo, M. (2014). A unified ant colony optimization algorithm for continuous optimization. European Journal of Operational Research, 234(3), 597-609.
13. Tao, F., Laili, Y., & Zhang, L. (2014). Brief history and overview of intelligent optimization algorithms. In Configurable intelligent optimization algorithm: design and practice in manufacturing (pp. 3-33). Cham: Springer International Publishing.
14. Eiben, A. E., & Smith, J. (2015). From evolutionary computation to the evolution of things. Nature, 521(7553), 476-482.
15. Corning, P. A. (2022). A systems theory of biological evolution. Biosystems, 214, 104630.
16. Jaimes, A. L., Oyama, A., & Fujii, K. (2013, June). Space trajectory design: Analysis of a real-world many-objective optimization problem. In 2013 IEEE Congress on Evolutionary Computation (pp. 2809-2816). IEEE.
17. Trojovský, P. (2023). A new human-based metaheuristic algorithm for solving optimization problems based on preschool education. Scientific Reports, 13(1), 21472.
18. Ye, X., Liu, S., Yin, Y., & Jin, Y. (2017). User-oriented many-objective cloud workflow scheduling based on an improved knee point driven evolutionary algorithm. Knowledge-Based Systems, 135, 113-124.
19. Chang, Y. (2025). The Application of Algorithm Optimization and Big Data Processing in Higher Education Management. International Journal of High Speed Electronics and Systems, 2540473.
20. Xu, X. (2025). AI optimization algorithms enhance higher education management and personalized teaching through empirical analysis. Scientific Reports, 15(1), 10157.
21. Wang, J., Yang, Y., Liu, H., & Jiang, L. (2024). Enhancing the college and university physical education teaching and learning experience using virtual reality and particle swarm optimization. Soft Computing-A Fusion of Foundations, Methodologies & Applications, 28(2).
22. Hill, H. C., Umland, K., Litke, E., & Kapitula, L. R. (2012). Teacher quality and quality teaching: Examining the relationship of a teacher assessment to practice. American Journal of Education, 118(4), 489-519.
23. Huang, J. (2021). An Internet of Things Evaluation Algorithm for Quality Assessment of Computer-Based Teaching. Mobile Information Systems, 2021(1), 9919399.
24. Weimin, O. (2021). Classroom education effect evaluation model based on MFO intelligent optimization algorithm. Journal of Intelligent & Fuzzy Systems, 40(4), 6791-6802.
25. Popescu, D. A. (2025). An Enhanced Genetic Algorithm for Optimized Educational Assessment Test Generation Through Population Variation. Big Data and Cognitive Computing, 9(4), 98.
26. Thaher, T., Zaguia, A., Al Azwari, S., Mafarja, M., Chantar, H., Abuhamdah, A., ... & Sheta, A. (2021). An enhanced evolutionary student performance prediction model using whale optimization algorithm boosted with sine-cosine mechanism. Applied Sciences, 11(21), 10237.
27. Ma, W., & Yang, Z. (2020, September). Evaluation of teaching quality in higher vocational colleges based on quantum behaviour particle swarm optimization. In Journal of physics: conference series (Vol. 1629, No. 1, p. 012042). IOP Publishing.
28. Moazeni, A., Khorsand, R., & Ramezanpour, M. (2023). Dynamic resource allocation using an adaptive multi-objective teaching-learning based optimization algorithm in cloud. IEEE Access, 11, 23407-23419.
29. Ying, G., & Fu, Y. (2023, August). Optimal Allocation of Higher Education Resources Based on Fuzzy Particle Swarm Optimization Algorithm. In EAI International Conference, BigIoT-EDU (pp. 48-59). Cham: Springer Nature Switzerland.
30. Xiao, S. (2023). English teaching resources recommendation based on improved ant colony optimization algorithms. Procedia Computer Science, 228, 464-476.
31. Li, H., Zhong, Z., Shi, J., Li, H., & Zhang, Y. (2021). Multi-objective optimization-based recommendation for massive online learning resources. IEEE Sensors Journal, 21(22), 25274-25281.
32. Li, W., & Fu, X. (2025, June). Research on the Optimization of Smart Teaching Resource Allocation in Higher Education Based on PSO Algorithm. In Proceedings of the 2025 International Conference on Management Science and Computer Engineering (pp. 199-205).
33. Zhang, X. (2021). Planning the structure of university teaching staff based on multiobjective optimization method. Scientific Programming, 2021(1), 1773561.

34. Gupta, S., & Sinha, S. (2020). Academic Staff planning, allocation and optimization using Genetic Algorithm under the framework of Fuzzy Goal Programming. Procedia Computer Science, 172, 900-905.
35. Fieldsend, J. E. (2017, July). University staff teaching allocation: formulating and optimising a many-objective problem. In Proceedings of the genetic and evolutionary computation conference (pp. 1097-1104).