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Research on the Path of Integrating University English Teaching Resources Using Data Mining Technology under Digital Transformation

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Abstract Under the background of digital transformation, the integration and sharing of university English teaching resources face challenges such as low efficiency and insufficient matching. This paper takes data mining technology as the core and combines blockchain technology to construct an English teaching resource sharing system. A semantic feature segmentation method based on decision tree is proposed, and a support degree calculation model is designed to realize accurate recommendation and safe sharing of resources. Through experimental verification, the algorithm in this paper, compared with the α# algorithm with sub-optimal performance, improves the completeness by 6.93%, the accuracy by 20.07%, the symbolicity reaches 1.9017, and the performance is optimal in all three dimensions. After the system in this paper was put into use, students' satisfaction with English teaching resources sharing increased from 54.56% to 81.62%. The one-way ANOVA of students in different majors has a significant difference, and the satisfaction of humanities majors is significantly higher than that of social sciences majors, P=0.017. The data-driven resource integration path can effectively solve the problem of teaching resource decentralization, and provide a technical reference for the digital transformation of education.

Index Terms English teaching resources, data mining technology, blockchain, decision tree, resource sharing

I. Introduction

In today's English education business more and more educational methods continue to emerge, the traditional university English teaching mode can not adapt to the development of the times, continue the traditional mode of teaching will only reduce the students' interest in learning and the ability to develop the English language [1]-[3]. In the information technology environment, college English should be constantly in line with the teaching of modernized and informatized educational methods, and change the original way of education [4], [5]. After continuous exploration and practice in recent years, the teaching mode of college English based on multimedia and network environment has been basically formed, and major universities have not only set up multimedia classrooms, network independent learning rooms and teaching resource libraries, but also informatized and networked digital campuses have also been built and are becoming more and more perfect [6]-[8]. These teaching resources can be used as an important cornerstone to build a platform for college English teaching, which provides a strong guarantee for improving the quality of college English teaching [9], [10].

With the continuous deepening of the English teaching reform, the current university English teaching mode has also exposed many problems that deserve calm reflection and need to be solved urgently, one of which is the integration of teaching resources [11]. The so-called resource integration is to reorganize and coordinate the existing limited resources so that the limited resources can play an unlimited role [12]. For the integration of university English teaching resources, it is through the full mobilization of all the resources that are conducive to the development of university English, such as on-campus and off-campus, and the integration of the collected resources by using certain means of coordination, so as to achieve the optimization of resources, and to achieve the success of students' education under the role of limited English resources [13]-[15]. Positively and steadily promote the integration of university English quality educational resources in universities has become an inevitable choice for the sustainable development of higher education in the information age.

In this paper, we first analyze the application of data mining technology in resource screening, and propose a feature segmentation model and support degree calculation method based on decision tree. It designs the English teaching resource sharing system architecture containing user layer, service layer and management layer, and combines blockchain technology to guarantee the safe sharing of resources. Select α algorithm, α++ algorithm and α# algorithm as the comparison model for comparative analysis to examine the performance superiority of this paper's algorithm in different dimensions. The students of colleges and universities in A university city in a certain city are taken as research objects to study the practical application effect of the system.

II. Construction of English Teaching Resource Sharing System Supported by Data Mining Technology

With the acceleration of education informatization, the integration and sharing of university English teaching resources has become a key issue to improve teaching quality. However, the traditional resource management model has problems such as data silos, low matching efficiency and high cost of manual screening, which urgently needs technical empowerment to realize the intelligent transformation of resource utilization. In this context, data mining technology has become an important tool for solving the problem of resource integration due to its ability to analyze massive data and its pattern recognition advantage.

II. A. Data Mining and Resource Selection

In the integration of university English teaching resources, the application of big data technology provides an unprecedented opportunity for English education, especially in data mining and resource screening. Data mining technology can extract valuable information from massive educational data and help students quickly locate resources suitable for specific needs. Data mining technology can automatically analyze students' learning behavior and effectiveness data to provide them with personalized teaching suggestions. For example, if a student has difficulty in reading comprehension, data mining technology can be used to find specific discourse materials that can improve reading comprehension. From the teachers' perspective, teachers need to spend a lot of time manually searching and screening teaching resources and it is difficult to ensure the quality and relevance of the resources, while big data technology can automatically screen and categorize a huge amount of online resources, and quickly locate high-quality resources that meet the teaching requirements. For example, teachers can search for original English articles, video lectures, online interactive exercises, etc., which are closely related to the current teaching topic through the big data platform, and then stimulate students' learning interest and enthusiasm through these resources.

II. B. English Teaching Resources Mining

II. B. 1) Information Semantic Feature Segmentation

Define the English teaching resource repository as d_n, segment it according to the keywords of English words as well as resource types, and segment it into k data subsets A_k by adaptive equalization segmentation method with its own characteristics $|d_{n-\max} - d_{n-\min}|(1/k)$, and A_k satisfies the condition: $A_1 \cup A_2 \cup \cdots \cup A_k = A$, i.e., the set of semantic feature concatenation of English teaching resources. Since the environment and the scope of use of English teaching resources are also different, for each environment to build a network model that meets its conditions, so that the state distribution of English teaching resources can meet the conditions: $A_i \cup A_j = \Omega_{ij}$, Ω_{ij} denotes the set of state distribution, $i, j = 1, 2, \cdots, k$ and $i \neq j$. After completing the above operations, the access control model for feature mining of English teaching resources is then built based on the decision tree model.

First, an empty node root is selected as the root node according to the semantic features, and the branch structure model is constructed at the corresponding parent node, and the rule data set is utilized to match the two nodes for computation within the resource library. Then node C: 0.8 is used as the search node for calculation, the adaptive probability distribution value of semantic feature segmentation can be obtained as 0.56. Based on 0.56, the decision tree model is constructed, and the result of semantic feature segmentation of English teaching resources can be obtained as shown in Equation (1):

$$H(x) = \sum_{k=1}^{K} p_k \ln \frac{1}{p_k} = -\sum_{k=1}^{K} p_k \ln p_k \tag{1}$$

where $H(x)$ denotes the semantic feature segmentation function, and the output of the function is the segmentation result; x denotes the amount of English teaching resources; K denotes the number of times of semantic segmentation in English teaching resources; and p_k denotes the value of the posterior probability distribution of the semantic feature segmentation of the English teaching resources, which is a poor value. According to the calculation result of Eq. (1), the semantic feature segmentation of English teaching resources information can be realized.

II. B. 2) Calculation of support for data items

The support function of the itemset I in the ELT repository D is denoted by $\varphi_D(I)$, $\min\sup$ that is, the value of the minimum support function, and $|T|$ denotes the scale size of the transaction T in the repository, that is, the number of resources contained in T. The length of the itemset d is denoted by $|d|$.

Theorem 1: The size of the ELT repository D is fixed, and the frequency of occurrence of the itemset I is independent of the resources whose size is smaller than $|I|$ (no proof process).

Theorem 2: There exists a frequent s-item set I_s (i.e., $\varphi_D(I_s) \geq \min\sup$) in the repository D such that the repository $D' = \{d \mid d \in D \wedge |d| \geq l > s\}$, and suppose that $\varphi_{D'}(I_s) < \min\sup$, then there exists a frequent l-itemset I_l in the repository D and $I_s \not\subset I_l$.

Proof: verify by applying the counterfactual method.

Suppose $I_s \subset I_l$.

If $d \in D$ and $|d| < l$, then $\varphi_D(I_l)$ does not affect whether or not there is a d itemset in the repository.

So $\varphi_D(I_l) = \varphi_{D'}(I_l)$, and because I_l is a frequent itemset, $\varphi_{D'}(I_l) \geq minsup$.

Since a subset of a frequent term set is also a frequent term set, $\varphi_{D'}(I_s) \geq minsup$, which contradicts the precondition, the proof is complete.

Theorem 3: Based on the above reasoning process, the support of the frequent s-itemsets $item_i$ and $item_j$ are computed separately to obtain the binary sets $(i_s, i_{s+1}, \cdots, i_q)$ and $(j_s, j_{s+1}, \cdots, j_q)$, i.e., there are $\sum_{p=s+1}^{q} \min(i_p, j_p) \geq \min\sup$ and $\left|item_i \cap item_j\right| = s-1$ is one of the indispensable conditions for constituting a repository.

Proof: since two frequent s itemsets have $\left|item_i \cap item_j\right| = s-1$, $\left|item_i \cup item_j\right| = s+1$.

Assuming that the probability values of $item_i$ and $item_j$ appearing in the set of items of size l in the repository D are r_i and r_j, respectively, and $l > s$, then the maximum probability values of $item_i$ and $item_j$ appearing in the set of items of size l are $\min(r_i, r_j)$.

Therefore, when $\sum_{p=s+1}^{q} \min(i_p, j_p) < minsup$, $item_i$ and $item_j$ do not belong to the necessary conditions for constituting a repository.

The necessary conditions are verified, ending the verification computation.

From the assumptions of Theorem 1, it can be seen that when calculating the support degree of the length is larger than the item set s, it is not necessary to continue to solve the item set with a length larger than s. Therefore, through the support degree calculation, the information with a size larger than s can be deleted from the resource base while determining the set constituted by the item set s, i.e., the information with a larger complexity or computation is deleted, which is convenient for the later English teaching resources to be efficient mining of English teaching resources in the later stage.

Assuming that L_s is the set of itemsets s, and $LC_s \subseteq L_s$ is the seed itemset, and the set of potential itemsets is obtained by calculating LC_s, the size of LC_s has a direct impact on the overall computational efficiency of the algorithm.

In the process of support calculation for data items of English teaching resources, since it is a segmented calculation, through the assumptions of Theorem 2, given a frequent u-item set constitutes an upper bound of the length l_{umit}, then it can be obtained that $\sum_{i=s}^{q} f_u > minsup$, and at this time l is an upper bound.

A relatively minimal upper bound can also be found by the above method, and the upper bound found here does not represent the final upper bound of the algorithm. Through the assumptions of Theorem 3, the constraints of frequent term sets are obtained, which also ensure the mining accuracy of English teaching resources to a certain extent.

II. C. Sharing of English Teaching Resources

II. C. 1) Framework basic structure

This paper constructs an English teaching resource sharing system, whose specific structure is shown in Figure 1. By analyzing the structure of educational resources and the demand for safe resource sharing, the basic structure of the framework is divided into three parts: the user layer, the service layer, and the management layer, in which the user layer can use the functions of the service layer to carry out the corresponding operations, while the management layer mainly manages the system in order to realize safe resource sharing.

(1) User Layer

The user layer includes not only the service recipients of resource sharing (resource users), but also resource providers, such as large-scale institutional databases and individual resource sharing. Therefore, users can be both resource users and resource providers.

(2) Service Layer

The service layer mainly includes the main functions realized by the system, including uploading, browsing and downloading of resources. Users carry out corresponding operations through the corresponding function modules in the service layer to meet their own needs.

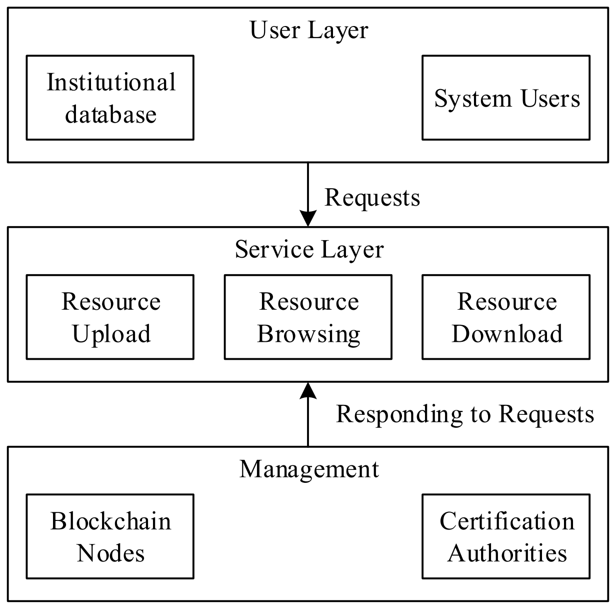

Figure 1: English Teaching Resource Sharing System

(3) Management

In the established framework for sharing educational resources, the management layer, through the relevant technology of blockchain, manages and maintains the educational resources through multiple institutional members and users who jointly form the nodes of the chain, so as to carry out the free circulation and exchange of educational resources within a certain range, realize their safe sharing, and break down the information barriers. The authentication agency in the blockchain acts as an agent for all nodes to manage the system, but all operations of the authentication agency will be broadcast in all nodes through the consensus mechanism in order to realize the consistency of the data and operations; the identity authentication service is carried out through the identity management mode of the blockchain network itself, and all nodes entering the system have to carry out identity authentication, and only through the authentication can they carry out the corresponding user operations.

II. C. 2) Resource-sharing processes

Set the institutional database resource sharer as $V1$, set the individual resource sharer as $V2$, and the resource user as U, and utilize the transaction process between $V1$, $V2$ and U to specify the process of educational resource sharing among different users:

First, the institutional database $V1$, individual resource sharers $V2$ and resource users U are authenticated through the blockchain to become member users of the educational resource sharing framework.

Second, the resource upload process is divided into two parts: (1) Institutional database $V1$ uploads resources, $V1$ uploaded shared resources are divided into two parts, the index information of the shared resources is stored in the blockchain, and the information of the address of the resources corresponding to each index is put into the cloud storage and encrypted. (2) The resources uploaded by individual resource sharers $V2$ are also divided into two parts, the blockchain stores the relevant information of the shared resources including the resource processing authority, content summary, time information, and the real data address, etc.; and the other part is the source data of the shared resources, which is encrypted and stored in the database. All resource sharers can set their personal transaction records in encrypted or public form according to their needs, and if encrypted, the public key they upload is utilized for encryption.

Third, the transactions of the certification authority and the transactions in the blockchain are confirmed through the consensus mechanism, and the nodes confirm the transaction information by broadcasting among themselves, updating the local ledger information, and checking the validity of the local ledger and whether it has been tampered with at certain intervals.

Fourth, the resource user U purchases resources and sends a request to the blockchain, including information about the resource requestor, a summary of the resources purchased, etc. After the blockchain consensus mechanism broadcasts the request to all the nodes and confirms it, and hands the transaction over to the certification body for the modification of the resource user U 's authority.

Fifth, according to the transaction information, the certification authority will unlock the authority of the corresponding resources, and at the same time decrypt the resource request information and send the resource address information obtained through the blockchain to the resource user U , who will obtain the shared resources according to the resource address to complete the sharing process.

Sixth, when the resource sharer U obtains the address information in the institutional database $V1$ and requests resources from the institutional database $V1$ via the resource address, the resource database $V1$ will first query the corresponding resource user U 's transaction information and the corresponding permission information in the blockchain network, and then open up the interface to allow the resource user to download the shared resources after confirming that there is no error. Sharing resources.

III. Analysis of the Effectiveness of English Teaching Resource Sharing Path Driven by Data Mining Technology

III. A. Analysis of experimental effects

III. A. 1) Comparative analysis of algorithms

The resource data consumed by the English Teaching Resource Sharing System designed in this paper is selected for implementation when it runs for 15 hours and processes 10TB workload in a certain time period. The experimental data are shown in Table 1. The data integration, data processing, and data interpretation modules consume 4h, 5h, and 6h respectively.

Table 1: Resource consumption data during a certain period of time

Module name	Time	Memory consumption/%	Bandwidth consumption/MB	CPU consumption/%
Data integration	2024.12.1 9:00	1.286354	783.072424	4.072423
	2024.12.1 9:30	1.289774	984.826424	3.049288
	2024.12.1 10:00	1.246757	823.927648	5.398621
	2024.12.1 10:30	1.248693	763.907313	4.973242
	...	...	...	...
	2024.12.1 13:00	1.208678	889.398632	5.386544
Data processing	2024.12.1 13:00	1.287533	32.592374	58.297342
	2024.12.1 13:30	1.284164	27.530753	60.496724
	2024.12.1 14:00	1.286543	31.440265	77.297242
	2024.12.1 14:30	1.308964	64.312986	80.981634
	...	...	...	...
	2024.12.1 18:00	1.309785	80.298652	68.329864
Data interpretation	2024.12.1 18:00	56.393224	18.248964	3.827542
	2024.12.1 18:30	74.397211	32.974243	7.074224
	2024.12.1 19:00	60.027831	68.386356	5.196423
	2024.12.1 19:30	52.497323	21.478524	4.872424
	...		...	...
	2024.12.2 0:00	78.296424	18.396435	6.035792

From the overall data distribution, the modules show significant resource consumption variability. In the data integration session, the system exhibits bandwidth-intensive characteristics, and its bandwidth consumption continues to be at a high level, with a peak value of 982.53MB, while the CPU and memory resource occupancy is relatively stable, remaining at about 2%-6% and 1.2~1.3%, respectively. This characteristic indicates that the module has a strong dependence on network bandwidth during data transmission, which is related to the real-time interaction demand of English teaching resources data. The data processing module, on the other hand, exhibits typical computationally intensive characteristics. Its CPU resource consumption shows a fluctuating growth over time, from 32.59MB in the initial stage to 80.30MB in the peak, reflecting the high occupancy of computing units during the execution of complex algorithms. The module's memory consumption is always kept at a very low level, and the data processing mechanism effectively avoids redundant data storage. In contrast, the resource utilization characteristics of the data interpretation module are more complex. The memory consumption shows dramatic fluctuations, while the CPU consumption is always in a low range. This indicates that the computational intensity of this module is relatively limited, and its resource bottleneck is mainly focused on the memory management level.

A good data mining model responds to the dependencies of the event activities in the software license logs, and the higher the degree to which the resource consumption event activities recorded in the software license logs match the data mining model, the higher the completeness of this model. Completeness refers to the percentage of resource consumption dependencies constructed by the model over the entire model for the resource consumption event activities recorded in the software license log. Assuming that n is the sum of all resource consumption event activities in the software license log, the completeness fitting formula for measuring the model is:

$$F_{complete} = \frac{(n-m) - punishment}{n} \times 100\% \tag{2}$$

$$punishment = \sum_{i=1}^{m} \frac{q_i}{p_i} \tag{3}$$

where m is the resource consumption event activity not embodied in the model, p_i is the resource consumption event activity recorded in the software license log, and q_i is the resource consumption event activity embodied in the model.

In order to accurately reflect the dependencies of resource consumption event activities in software license logs, it is necessary to consider not only the data mining model itself, but also pay attention to the parallelism and selection structure among models. Assuming that $n(a \|_w b)$ is the number of times the parallel relationship between a events and b events in the software license log occurs, and $n(a \#_w b)$ is the number of times the selective relationship between a events and b events in the software license log occurs, the formula for measuring the accuracy of the model is:

$$F_{precise} = \left| \frac{n(a \|_w b)}{n(a \|_w b) + n(a \#_w b)} - P \right| \times 100\% \tag{4}$$

where P is the a priori probability of the occurrence of parallel relationships.

From both completeness and accuracy, it can be seen that the higher the completeness of the model, the higher the accuracy if the model is able to better reflect the relationship between the resource consumption event activities recorded in the software license logs. Conversely, the worse the completeness, the worse the accuracy. Therefore, measuring the compliance of the process model needs to combine the weighted values of completeness and accuracy.

The mainstream algorithms α algorithm, α++ algorithm, and α# algorithm are used as comparison models, and the experimental results are compared and analyzed using completeness, accuracy, and compliance. The experimental results of this paper's algorithm and the comparison algorithm are shown in Table 2. The proposed algorithm improves completeness by 6.93%, accuracy by 20.07%, and significance by 1.9017 compared to the sub-optimal performance of α# algorithm, which is optimal in all three dimensions of performance. It verifies the effectiveness of the design of the system support algorithm in this paper, which can have better data mining results.

Table 2: Comparison of Experimental Results

	Quantitative analysis		Qualitative analysis
	Integrity	Accuracy	Conformity
α algorithm	68.42%	55.38%	1.2964
α++ algorithm	77.22%	61.47%	1.3875
α# algorithm	88.35%	75.86%	1.4989
The proposed	95.28%	95.93%	1.9017

III. A. 2) Patterns of change in resources

The macroscopic display of the change trend of CPU, memory and bandwidth resources during system operation is shown in Figure 2. The system running process can be roughly divided into three cycles according to the changes in resource consumption, respectively, before, during and after, which corresponds to the alternating and iterative operation of the three modules of the system, and also corresponds to the life cycle of the system running. In the early stage, the transition of the system from the initial state to the running state will inevitably increase the consumption of CPU and bandwidth resources; in the middle stage, when the system is running smoothly, the consumption of resources is also relatively stable; with the execution of the task approaching the end, the read/write rate at this time also slowly decreases from faster to smaller, and the demand for resources also gradually decreases from more to less.

To summarize, when the system is just starting to execute tasks, the supply of CPU, memory and bandwidth resources should be increased. When the system is running in the middle stage, the dynamic changes in the consumption of each resource are combined to dynamically implement different supply quantities for different resources. At the end of the system's operation, the supply of CPU, memory and bandwidth resources should be increased appropriately to ensure the smooth operation of the system.

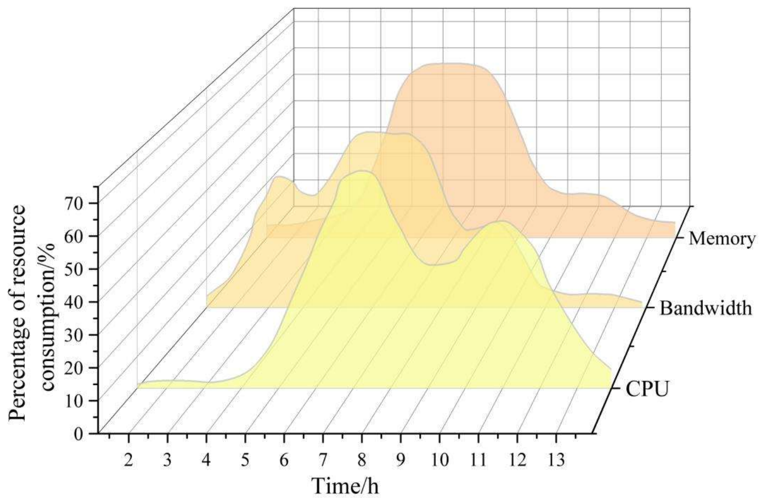

Figure 2: Variation trend of CPU, memory and bandwidth resources

III. B. Analysis of application effects

This study takes the students of universities in A university city of a certain city as the research object, and adopts the pre- and post-test questionnaire survey method to investigate the application effect of the university English teaching resource sharing system in the context of digital transformation. At the beginning of the experiment, 1,200 students were selected through stratified random sampling, covering different grades, majors and English proficiency levels to ensure the representativeness of the sample. The first questionnaire distribution focused on the status quo of shared resource use, and 1126 questionnaires were effectively recovered after data cleaning, with an effective rate of 93.83%.

III. B. 1) Basic information on shared resources

The basic situation of the use of English teaching shared resources by college students in University City A is shown in Figure 3. In this survey, 38.42% of the college students have not used the shared resources in the university city, while the percentage of the number of users of each type of shared resources has an obvious gradient characteristic, with the first gradient being course lecture resources (30.27%), the second gradient being book resources (19.01%) and campus website resources (18.44%), and the third gradient being study room resources (7.84%) and laboratory resources (5.11%). It can be seen that college students in University Town A use less English teaching shared resources, the sources of shared resources are more limited, and their access to shared resources is limited.

III. B. 2) Analysis of satisfaction with shared resources

Based on the results of the preliminary analysis, the research team put the designed English teaching resource sharing system into use by embedding it into the campus networks of the universities in University City A. The system was used to share resources with the students. After 8 weeks of practice implementation, a revised questionnaire was distributed to the same group of subjects, focusing on assessing students' satisfaction with the resource sharing system and exploring the effect of resource sharing after adopting the system optimization. The satisfaction of university students with English teaching resources sharing before and after the practice is shown in Figure 4. After the practice, students' satisfaction with English teaching resources sharing increased from 54.56% to 81.62%, which is a more significant improvement. The English teaching resource sharing system designed in this paper can improve the convenience and efficiency of resource access, and effectively optimize students' resource access path.

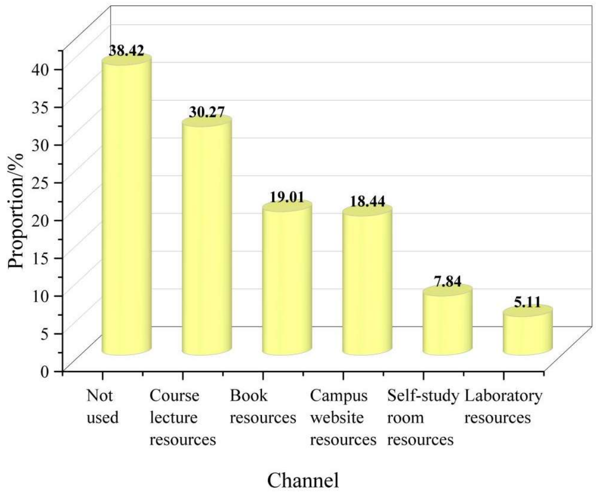

Figure 3: Basic situation of the use of shared resources

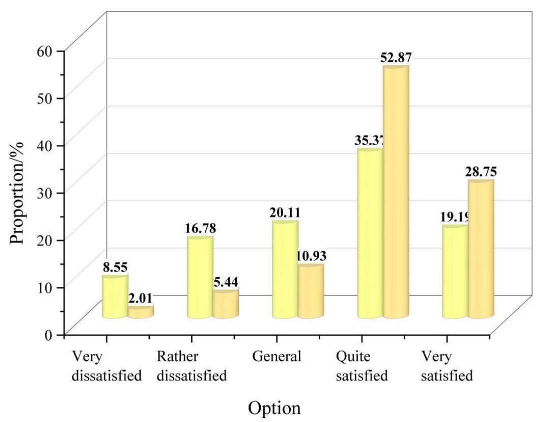

Figure 4: Comparison of satisfaction situations

The t-test was used to unfold the analysis of variance of students' gender, education, major and resource satisfaction, and the results of the analysis of variance are shown in Table 3. The independent samples t-tests of students of different genders and academic degrees did not have significant differences, and the one-way ANOVA of students of different majors had significant differences, and the satisfaction of students of humanities, social sciences, and science and engineering majors before the practice was 3.68±0.93, 3.22±0.77, and 3.25±0.89, respectively, with F=8.083 and P=0.003. The post-practice satisfaction of humanities, social sciences, and science and engineering majors was 4.13±0.78, 3.89±0.73, and 3.91±0.49, respectively, F=5.018, p=0.017.

Further LSD post hoc multiple comparisons of one-way ANOVA of professional variables and resource satisfaction were developed and the results of the analysis are shown in Table 4. Pre-practice satisfaction was significantly higher for humanities majors than for social sciences and science and technology majors, P<0.01, and in terms of post-practice satisfaction, humanities majors were significantly higher than social sciences majors, P=0.017.

Table 3: Results of Differential Analysis

Individual characteristics		Satisfaction before practice	Satisfaction after practice
Gender	Male	3.44±0.78	4.04±0.62
	Female	3.36±0.97	3.95±0.76
	t	0.637	0.538
	P	0.782	0.601
Educational background	Undergraduate	3.42±0.97	4.02±0.83
	Graduate student	3.39±0.73	3.98±0.95
	t	0.801	0.673
	P	0.735	0.566
Professional	Humanities	3.68±0.93	4.13±0.78
	Social sciences	3.22±0.77	3.89±0.73
	Science and Engineering	3.25±0.89	3.91±0.49
	F	8.083	5.018
	P	0.003	0.017

Table 4: One-way Analysis of Variance

Dependent variable	Major Category 1	Major Category 2	Average value difference	Standard error	Significance
Before practice	Humanities	Social sciences	0.46	0.12	0.000
		Science and Engineering	0.43	0.07	0.002
	Social sciences	Humanities	-0.46	0.12	0.000
		Science and Engineering	-0.03	0.09	0.731
	Science and Engineering	Humanities	-0.43	0.07	0.002
		Social sciences	0.03	0.09	0.731
After practice	Humanities	Social sciences	0.24	0.11	0.017
		Science and Engineering	0.22	0.05	0.218
	Social sciences	Humanities	-0.24	0.11	0.017
		Science and Engineering	-0.02	0.03	0.622
	Science and Engineering	Humanities	-0.22	0.05	0.218
		Social sciences	0.02	0.03	0.622

IV. Conclusion

In this study, a data mining technology-driven resource sharing system is constructed to address the pain points of university English teaching resources integration, and the effectiveness of the system design is examined through experiments.

Compared with the α# algorithm with sub-optimal performance, the algorithm in this paper improves the completeness by 6.93%, the accuracy by 20.07%, and the symbolism reaches 1.9017, which is the optimal performance in all three dimensions. It verifies the effectiveness of the system support algorithm design in this paper, which can have better data mining effect.

Based on the statistical results of 1126 questionnaire data, after the system of this paper is put into use, students' satisfaction with English teaching resources sharing increases from 54.56% to 81.62%. The one-way ANOVA of students of different majors has significant differences, and the satisfaction of students majoring in humanities, social sciences and science and technology after practice is 4.13±0.78, 3.89±0.73, 3.91±0.49, respectively, F=5.018, P=0.017. The satisfaction of humanities majors is significantly higher than that of social sciences majors, P=0.017.

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