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Personalized Learning Resource Push Evaluation Considering Image Big Data Processing Technology

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With the continuous development of the social economy, the ways of obtaining learning materials and learning resources have gradually increased, especially the development of the Internet has enabled more high-quality resources to be shared, but it should be noted that it is precisely because of the excessive resources, it is relatively complicated to find suitable and interesting learning resources. In response to these needs and deficiencies, this paper introduce image big data processing technology, characterizes specific learning characteristics using the time decay function by sorting out the business logic of personalized learning resource push. It also imports specific learning cognitive levels, and matches with the corresponding learning resources, maximizes the quality service of personalized Learning facilities, and improves the efficiency of learning resources. The study findings demonstrate that the image big data processing technique is effective and can support the push evaluation of personalized learning resources.

Povzetek: Prispevek ocenjuje personalizirano posredovanje učnih virov ob upoštevanju tehnologije obdelave slikovnih velikih podatkov. Z uporabo funkcije časovnega razpada za karakterizacijo učnih značilnosti in uvozom specifičnih učnih kognitivnih ravni se izboljša učinkovitost in kakovost posredovanja učnih virov. Študija potrjuje učinkovitost te tehnologije pri podpori ocenjevanja personaliziranih učnih virov.

1 Introduction

In the continual expansion of the economic system, individuals are more focused on learning, and the general teaching quality and the number of audiences have also increased accordingly [1–2]. In addition to the traditional paper learning materials, the advancement of online technology has contributed to greater online learning resources being shared online. Consequently, the Internet provides access to corresponding learning resources. On the one hand, users can mine the learning resources they are interested in, such as MOOCs, Learning Power, etc.; on the other hand, users can upload their materials for sharing, so that the learning resources form a closed loop. This shows that for Internet learning resources, users are both users and sharers of learning resources. Starting from individual nodes, a fixed connection between the teaching and analysis of network learning can be achieved [3–4]. Scholars within the industry have carried out in-depth research on this and believe that the basis for sharing learning resources should be a learning and teaching environment for different users to achieve personalised applications. Through specific teaching methods such as reorganisation and extraction, personalised resource learning is realised to maximise the exchange and sharing of knowledge and information, to achieve personalised learning and sharing, to build a corresponding learning environment, and to maximise the utilisation of learning resources, aiming to solve the problem of limitations in Internet online resource learning [5–6].

However, it should be noted that, among the numerous learning resources, how to effectively extract the information that is of interest and useful to you depends on the specific recommendation method. Industry experts have carried out extensive research on this topic, frequently applying this targeted recommendation method in areas such as e-commerce shopping, personalized news browsing, personalized book recommendations, and music recommendations. For the field of pedagogy, personalized specific recommendations can be used to often make specific recommendations based on specific recommended content, the user's browsing history, and hobbies; or the user's learning style and points of interest are used to make comprehensive and collaborative recommendations. In addition, some scholars use the similarity of analogy users and collaborative filtering of items to realize the recommendation of personalized learning resources; more scholars use the effective generation and specific evaluation of personalized learning paths, focusing on analyzing the knowledge level of users, personal ability and personality characteristics for theme-based recommendations. These personalised recommendation algorithms achieve the purpose and needs of user retrieval to a certain extent, but there are still certain limitations. For example, the recommendation method mainly focuses on the relationship between users and specific resource binary structures, but learning resources are not fragmented, independent entities but interrelated. In the process of recommendation, it is vital to evaluate the link between resources, information systems, and users. From the perspective of the learning process, learners often overlook the importance of timing. The resources used to gain knowledge are constantly supplemented, updated, and changed. These temporal changes may contain concerns that learners are interested in, which may not be in line with the actual learning and cognition process. To satisfy the interests of users but also to meet the specific cognitive learning resources of users, from the beginning to the final mastery, comprehensive consideration is required. Improving the use efficiency of learning resources, aiming to improve the quality and effect of self-learning, and providing users with knowledge that is more suitable for their cognitive level are all goals of this study. The study accomplishes these goals by conducting a business logic analysis of personalized learning resource push, representing learning characteristics specifically, quantitatively estimating cognitive level, matching existing learning resources, and realizing a specific push of online learning resources. Table 1 depicts the summary table of related works.

Table 1: Related works

Research Study	**Methodology Overview**	**Strengths**	**Limitations**
[27]	This study delves into the evolving intersection of personalized learning and Internet technology within the education domain. Leveraging network technology, the research introduces a groundbreaking approach: a personalized information push system based on recommendation. Algorithms.	The system excels in providing personalized learning resources, tailoring recommendations based on users' usage history and tag attribute characteristics.	While the integration of clustering algorithms enhances performance, it introduced a level of algorithmic complexity that may require careful implementation and consideration.
[28]	In response to the rapid evolution of big data, this study explored the extensive development of artificial intelligence teaching systems, which have become integral tools for independent learning in diverse university settings.	The system offered a wealth of learning resources and tools, contributing to a dynamic and enriched learning experience.	The effectiveness of the artificial intelligence teaching system is contingent on technological infrastructure, potentially posing challenges in resource-constrained environments.
[29]	This study explored the transformative potential of artificial intelligence technology in advancing personalized learning. Leveraging tag, index, and intelligent grabbing	The application of virtual reality, augmented reality, and hybrid reality technologies	Emotion analysis, while promising, can face challenges in accurately interpreting and responding to individual

	technology, the research focuses on the rapid acquisition of learning resources from a complex knowledge map.	contributes to the creation of personalized online learning classrooms, fostering immersive and engaging learning experiences.	emotions, as emotions can be nuanced and context-dependent.
[30]	The study recognized the increasing demand for personalized learning and explored the application of Personalized Recommendation (PR) technology to enhance learners' efficiency.	The study encompasses system requirements analysis, database design, functional module design, implementation, and testing, ensuring a comprehensive and well-structured approach to platform development.	The success of the personalized learning platform heavily relies on the effectiveness and sensitivity of the chosen CF algorithm, which may have limitations in certain scenarios.
[31]	In response to the challenges presented by the Big-data Era, this study focus on the construction of a precise personalized learning evaluation system to analyze learner behaviors and predict personalized learning performance.	The meticulous design of first, second, and third-level indicators provides a detailed and nuanced understanding of learners' behavior and performance.	The effectiveness of the learning evaluation system is contingent on the availability and quality of learning behavior data, which may pose challenges in certain contexts.

2 Image big data processing

The specific types of digital images mainly include the following:

(1) Black-and-white binary image type: Its main feature is that the relevant information on the map is either black or white, and this contrast is more obvious and stronger. In the storage process of the computer, even a single pixel, where each pixel contains 1 data bit, can identify at most 2 different gray levels. Black-and-white binary image types involve managing and analyzing large datasets of monochromatic images. This specialized processing deals exclusively with binary images, where pixels are either black or white, representing distinct visual information. Algorithms and techniques for this subset of image processing focus on tasks like pattern recognition, edge detection, and shape analysis. Within the broader scope of image big data, specific processing methods focus on black-and-white binary imagery to extract meaningful insights and patterns from this distinctive visual data format.

(2) The type of grayscale: This type of image is often divided into multiple gray levels, from black to white, and the transition between each gray level is relatively smooth. Therefore, this method often results in colors that users do not require in this type of image. Generally speaking, each pixel includes different long data, and the specific composition is realized by different devices. A maximum of 256 grayscale data sets can be identified. The type of grayscale refers to a crucial aspect involving the representation of image data. Grayscale images, devoid of color, utilize varying shades of gray to depict intensity levels. This type of processing involves interpreting and manipulating these intensity values, impacting image contrast in detail. Understanding and managing grayscale within the broader context of image big data processing is essential for tasks such as image analysis, recognition, and enhancement, contributing to more nuanced and sophisticated visual data interpretations.

(3) Colour type: Colour type in big data image processing refers to the classification and analysis of images based on their colour attributes. It involves extracting, categorizing, and processing vast datasets of images to discern colour patterns, enabling applications in fields like computer vision and image recognition. Understanding color types enhances image processing algorithms, aiding in tasks such as object detection and segmentation. This subset of image big data processing plays a pivotal role in decoding and utilizing the rich visual information embedded within diverse datasets. In an RGB color image, each pixel can express 16777216 colors.

On a specific computer, the representation of an image often includes drawing points and short polylines. The method of drawing points is to analyze the luminous discrete points on the data display screen and effectively combine the pixel points on the screen; the method of short polylines can realize specific grid image analysis [7–8].

For an image, the figure is the distribution response of the reflected and projected light of the object; the picture is human visual sensory cognition, so the figure exists in essence; the picture is the description of the sense; and the image realizes the effective integration of the essence and the senses. It is not enough to only regard the image as a two-dimensional or three-dimensional color distribution; the influence of human emotions and psychological factors also needs to be considered in specific image processing. Image processing is the effective processing and analysis of image information to achieve practical applications.

For computer image processing, it has three main characteristics, as follows:

- First, the image processing technology is comprehensive. In the corresponding computer processing process, basic knowledge of mathematics, physics, optics, etc. is often involved. At the same time, it also includes several technologies such as projection, photography, and display. The computer has become the main image processing method, so it is extremely important.

- The hardware of the computer improves the accuracy of the calculation. Depending on the actual application, we can increase the accuracy of image processing, which in turn improves the efficiency of the computer and the corresponding calculation accuracy.

- Personalized customization and strong flexibility. For image processing, it can effectively process any range and any size of the image.

In the actual personalized learning system, teachers and students are important components. Teachers are responsible for the effective construction and management of corresponding online resources and knowledge bases, and they can use ontology to carry out this task. The main process is to first construct two parts: the semantic library and the resource library. The semantic library is represented by the ontology concept to represent the specific knowledge points, and the attributes of the ontology are used to connect the knowledge points to form a specific semantic layer. The corresponding resource library is constructed by learning objects, which encapsulate fixed learning resources correspondingly, and conducts analysis through unique identification and positioning [9–10].

When students carry out specific learning, the system records according to the student's behavior, uses the learner to analyze the changes in the engine, realizes the specific learning process and effective access to online resources, and constructs the learner's knowledge structure and the corresponding cognitive level feature model. The corresponding recommendation engine is based on specific learning features and labeled learning resources, recommends according to specific recommendation algorithms, and uses the corresponding sorting order to recommend online resources, as shown in Figure 1:

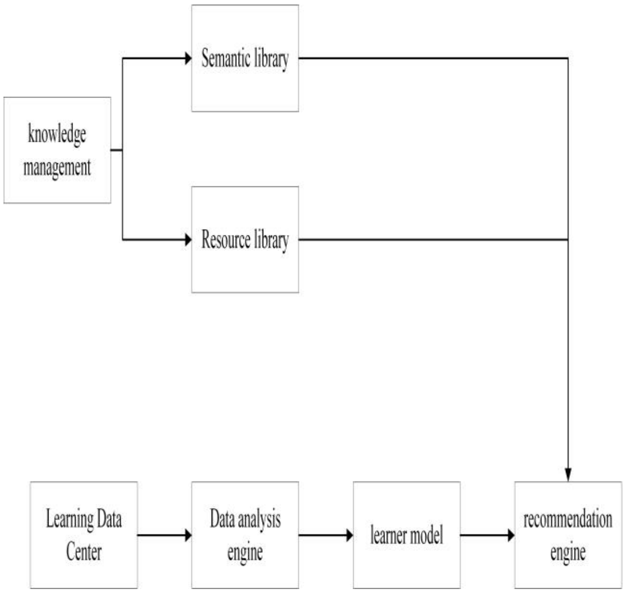

Figure 1: General architecture of a personalized learning system.

2.1 Definition of symbol

To effectively process big data, first define the initialization of symbols, as shown below:

(1) s_i : learner i, which means the learner with the unique identifier i;

(2) S: learner set $S = \{s_1, s_2, \cdots, s_m\}$, represents the set composed of m learners;

(3) o_j : used to represent the object of learning, that is, used to identify a unique object;

(4) O: the object set of learning, utilize the learning object to carry out the constitution of the concrete set;

(5) c_k : k used to identify the concept;

(6) C: Concept set $C = \{c_1, c_2, \cdots, c_p\}$, which represents the set composed of p concepts.

2.3 Formal representation of learner feature model

The formalization of the learner's specific feature model is to realize the abstraction of specific learning behavior and use the corresponding learning process for analysis. The visualization of the feature model is an important part of the whole process, and it is the basis of personalized recommendations. From the perspective of specific recommendations, the specific cognitive structure and level of learners can be achieved, mainly focusing on two specific perspectives, including the following:

It represents an effective transmission of learning elements. Learning is a dynamic process, during which learners can use different periods to learn content, and are constantly changing according to their knowledge structure. For example, if the learners already have a certain knowledge base, they can directly enter the subsequent learning without being bound by a specific knowledge point. This kind of transfer of interest points that can effectively characterize the learner needs to be captured effectively. To realize the characterization of the time of interest points, a corresponding index can be introduced as a specific variable of time decay[11-12].

Another aspect is the progressive nature of learning. According to the standards of human cognition and the concept of learning resource setting, the corresponding personalized recommended learning resources should conform to the specific cognition level of users. If the recommended learning resources are too complex or too simple, they cannot meet the needs of specific users, nor allow the user to truly grasp the specific situation. Therefore, a specific knowledge point can be used as an evaluation index of a specific ability to measure the user's effective grasp of the knowledge point or this type of knowledge point. The specific comprehensive considerations mainly include two categories: one is the correct rate of the user's answer, and the other is the difficulty of the question setting. The evaluation results are quantified into {1, 2, 3, 4, 5, 6} to achieve specific quantitative analysis.

2.4 Labelling of learning resources

Annotating semantic information for corresponding learning resources can effectively enhance the connectivity between learners and resources. The semantic features brought by this can be specifically expressed by formula (1):

$$V(o_j) = \left\{ c_y, dif\left(o_j, c_y\right) \middle| 1 \le x \le t, c_y \in Con\left(o_j\right) \right\} \tag{1}$$

From the specific architecture, it can be concluded that the recommendation engine is the core of the whole process, and the recommendation algorithm of online learning resources is the specific work content realized by the recommendation engine, which is mainly based on the association between learners and the corresponding learning resources. Meanwhile, it must be based on the feature representation of the integrated learner and the annotation of the corresponding online learning resources.
The essence of learning is a specific dynamic change process, which is sensitive to time factors, so it is necessary to fully consider specific time factors. For example, learners need to review the knowledge points they have already mastered while avoiding repetitive learning. In the real recommendation process, deeper knowledge points or more application fields should be recommended; if the original knowledge points continue to be pushed, it will be counterproductive. Thus, a time decay function is used for characterizing the actual variation of learning points of interest.

2.5 Time decay function

To effectively use the corresponding function to specifically characterize the time series characteristics of learning resources, the fluctuation of the time series can have a specific impact through the function. For the function value, the smaller the value, the longer the time, and vice versa, the closer the time, the calculated function value is. Therefore, the specific calculation of the time weight can be specifically expressed by formula (2):

$$W\_Time(s_i, c_x) = \frac{1}{\left(1+\mu DS\ pan\left(tim(s_i, c_{nearest}) - tim(s_i, c_x)\right)\right)} \quad (2)$$

Among them, the last time point of the learner is denoted by $tim\left(s_i, c_{nearest}\right)$.

After comparative analysis, it can be seen that when the function calculation value of the decay function reaches 1, it indicates that the interest of the learning point can best express the maximum learning interest point; if the function value gradually decreases with the specific time change, it reflects the learning activities in the recent period. The in recent corresponding learning objects are more likely to be recommended, more in line with specific logic, and have corresponding rationality.

2.6 The matching operator between learners' cognitive level and learning resource difficulty

For learning resources, the specific difficulty is related to the cognitive level of the learner, and the specific matching value is higher, and conversely, the matching value is reduced. Therefore, the matching between the interests of learners and online learning resources can be specifically calculated and expressed by formula (3):

$$\underset{\forall c_x \in M(s_i)\cap V(o_j)}{Match}\left(abi(s_i, c_x), dif(o_j, c_x)\right) = \frac{2abi(s_i, c_x)\cdot dif(o_j, c_x)}{abi(s_x, c_x)^2 + dif(o_j, c_x)^2} \quad (3)$$

From the calculation of formula (3), it can be found that if the specific difficulty and cognitive level are equal, the corresponding value is the largest; the larger the difference between the difficulty value and the cognitive level the smaller the corresponding calculated value.

2.7 Calculation of matching degree between learners and learning resources

The corresponding parameter settings are initialized, by calculating the matching degree $Rec\_Val\left(s_i, o_j\right)$ of the learner s_i and the learning resource o_j, as shown in formula (4):

$$Rec\_Val\left(s_i, o_j\right) = \sum_{\forall c_x \in M(s_i)\cap V(o_j)} \alpha W\_Tim(s_i, c_x) \cdot \beta Mathch\left(abi(s_i, c_x), dif(o_j, c_x)\right) \quad (4)$$

In the formula, α and β are adjustment factors, and the values of the two must satisfy ;

In the high-dimensional space, the classification hyperplane that separates the two types of samples without error satisfies, and the specific calculation is shown in formula (5):

$$\omega \cdot x + b = 0, x \in R^n, b \in R \quad (5)$$

Through the normalized analysis of the parameters, the specific classification interval analysis is carried out, and the specific analysis of the classification samples is carried out for the classification line, and the specific calculation is shown in formula (6):

$$y_i\left[\left(\omega\cdot x_i\right)+b\right]-1\geq 0, i=1,2,\cdots,n \quad (6)$$

Based on formula (6), the formula is converted, and the specific calculation is as shown in formula (7):

$$\Phi\left(\omega\right)=\frac{1}{2}\left\|\omega\right\|^2=\frac{1}{2}\left(\omega\cdot\omega\right) \quad (7)$$

Based on formula (7), the constraint conditions are calculated, as shown in formula (8):

$$\sum_{i=1}^{n} y_i a_i = 0, a_i \geq 0, i=1,2,\cdots,n \quad (8)$$

Under the condition (4), find the maximum value of the following functions for a_i, and the specific calculation is shown in formula (9):

$$Q\left(a\right)=\sum_{i=1}^{n} a_i-\frac{1}{2}\sum_{i,j=1}^{n} a_i a_j\left(x_i\cdot x_j\right) \quad (9)$$

The optimal classification function obtained by solving is, the specific calculation is shown in formula (10):

$$f\left(x\right)=\operatorname{sgn}\left\{\left(\omega\cdot x_i\right)+b\right\}=\operatorname{sgn}\left\{\sum_{i=1}^{n} a_i y_i\left(x_i\cdot x\right)+b\right\} \quad (10)$$

Based on formula (10), the conditions are relaxed, as shown in formula (11):

$$y_i\left(x_i\cdot\omega+b\right)\geq 1-\xi_i, i=1,2,\cdots,n \quad (11)$$

At the same time, a penalty term is introduced into the objective function, and the specific calculation is shown in formula (12):

$$\Phi\left(\omega,\xi\right)=\frac{1}{2}\left\|\omega\right\|^2+C\left(\sum_{i=1}^{n}\xi_i\right) \quad (12)$$

Based on formula (12), the setting transformation of constraints is carried out, as shown in formula (13):

$$\sum_{i=1}^{n} y_i a_i = 0, 0\leq a_i\leq C, i=1,2,\cdots,n \quad (13)$$

The inner product in high-dimensional linear space can be specifically calculated by formula (14):

$$K\left(x_i,x_j\right)=T\left(x_i\right)gT\left(x_j\right) \quad (14)$$

The three kernel functions that are currently used are as follows[13-14]:

(1) The specific calculation of the polynomial inner product function is shown in formula (15):

$$K\left(x_i,x_j\right)=\left[\left(x_i g x_j\right)+1\right]^q \quad (15)$$

(2) The specific calculation of the radial basis function is shown in formula (16):

$$K\left(x_i,x_j=\exp\left(-\frac{\left\|x_i-x_j\right\|^2}{\sigma^2}\right)\right) \quad (16)$$

(3) The specific calculation of the S-type inner product function is shown in formula (17):

$$K\left(x_i,x_j\right)=\tanh\left(v\left(x_i g x_j\right)+c\right) \quad (17)$$

Personalized learning resources based on students' self-learning feedback can better support students' self-improvement and self-learning, and promote their further development. The main online learning resources include two aspects:

(1) Students independently find and retrieve online learning resources that they are interested in;

(2) According to the corresponding learning evaluation information, carry out effective recommendations of students' online learning resources, and carry out resource allocation processing according to the actual situation, as shown in Figure 2:

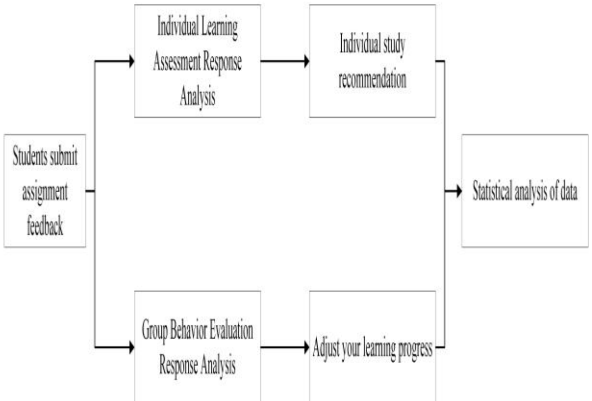

Figure 2: Personalized learning evaluation and resource push.

The specific online learning resource push needs to be determined according to the actual learning goals. The complete process mainly includes specific steps such as data sample collection, data preprocessing, training learning, specific evaluation classification, and pushing learning resources.

3 Simulation experiment

To effectively verify the effectiveness of the image big data processing technology, this paper selects the corresponding samples for processing and analysis and realizes the push analysis of personalized online learning resources.

3.1 Description of algorithm experiment process

(1) Constructing the knowledge base of "C language programming" course

①Build a semantic library

When constructing the semantic database, the concepts are expressed by the names of knowledge points, and some specific knowledge points are shown in Table 2.

Table 2: Knowledge point collection (part).

Name of knowledge point	Name of knowledge point
Type of data	Character string
Expression	Function
Input and output functions	Preprocessing command
Select statement	Pointer
Loop statement	Structure
Array	Document

②Annotation Repository

A specific resource library includes specific learning objects. The standard of data collection can be described concerning specific metadata, and the online learning resources encapsulated by it can be identified and effectively located through the network to achieve specific semantic labeling [15-16]. Some online learning resources are shown in Figure 3. According to a certain period of learning, specific learner feature vectors can be obtained.

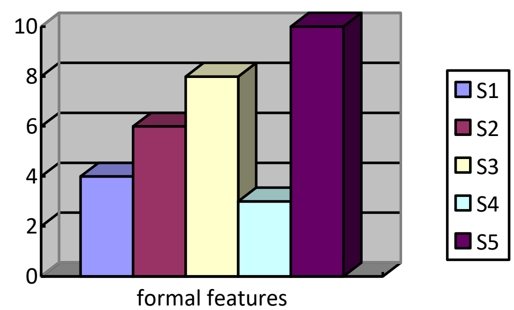

Figure 3: Learner formalization features.

According to the corresponding time function decay factor, the specific data is listed as shown in Figure 3.
It is evident from the findings in Figure 3 that the corresponding time function can better reflect the dynamic transfer characteristics of learning. According to the effective learning time point, the analysis of the characteristics is carried out. The greater the timeliness, the higher the possibility of being recommended. On the contrary, if the calculated value of the time function is smaller, the corresponding online resource is less likely to be recommended.
The matching operator of cognitive level and difficulty better reflects the cognitive principle of gradual learning. For the cognitive matching operator, when the difficulty of the learning resource is equal to the cognitive level, its value is 1. In this case, the online learning resources are more likely to be pushed; on the contrary, if the difference between the difficulty value and the corresponding

cognitive level is large, the corresponding recommendation probability is smaller [17-18].

The learning resources generated by the recommendation algorithm conform to the teaching experience of subject teachers.

After specific analysis, in the process of selecting corresponding indicators and constructing a specific evaluation model, it is still unable to reflect the real situation of specific learners intuitively and effectively. Secondly, for the coverage of samples, the data samples have certain limitations and cannot fully represent all situations; finally, the specific evaluation of learning is always artificial and subjective, so the evaluation systems constructed by different experts are different, unable to achieve the objective recognition rate as high as the image big data processing technology.

However, such a model has greatly improved the specific degree of automation and effectively improved the performance of automatic learning, personalized learning, and adaptive learning. At the same time, the complexity of the algorithm is relatively low, and it has the performance of real-time computing.

4 Resource acquisition form

It can be seen from the existing research results that more students tend to use professional learning applications APPs to search for and learn personalized resources. From the specific data samples, it can be seen that students still rely too much on traditional teaching classrooms for teaching resources, especially English teaching resources. Teachers in schools generally publish corresponding course resources through information-based teaching methods, which has become a common way to obtain online resources, specifically as shown in Figure 4:

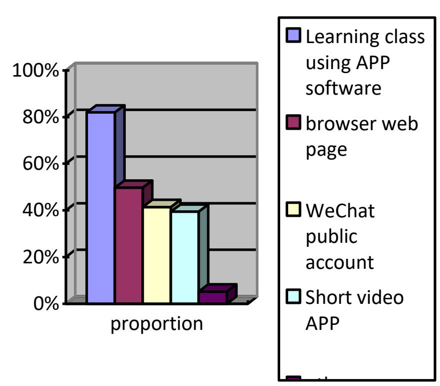

Figure 4: Acquisition form of English mobile learning resources for vocational college students.

4.1 Purpose of usage of resource

For specific students, the purpose of applying specific English learning resources is mainly as shown in Figure 5, in which the thirst for new knowledge accounts for the vast majority. In addition, the second purpose is to expand English knowledge outside the classroom, thus indicating that students even more expect to acquire knowledge of English outside the curriculum.

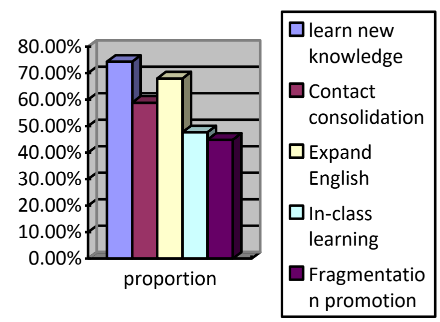

Figure 5: The purpose of using English mobile learning resources for vocational college students.

4.2 Motivation of usage of resource

From the results in Figure 6, it can be seen that the student's specific interest and love for English is more that learning English is the main driving force for acquiring mobile resources, indicating that the design and arrangement of English learning tasks will drive students to use mobile learning resources.

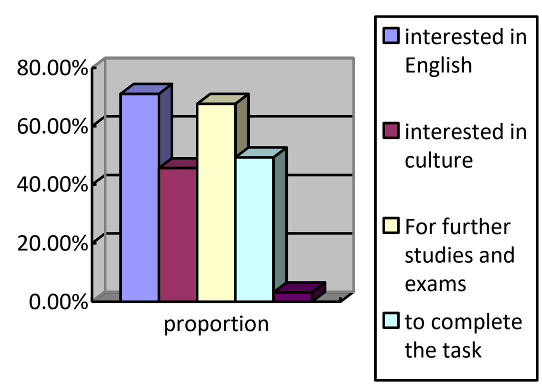

Figure 6: Motivation for vocational college students to use English mobile learning resources.

4.3 Type of resource requirement

Elemental learning of resource content is a core component of online resources. Using the analysis of students' needs for learning English resources, we can clearly understand how to integrate, pool, and drive learning resources through image big data processing, to match resources and needs and improve the utilization rate and effect of English learning [19-20]. Specifically, as shown in Figure 7. In addition, due to the different foundations of students, it is necessary to allow students to carry out effective review and development through corresponding resources.

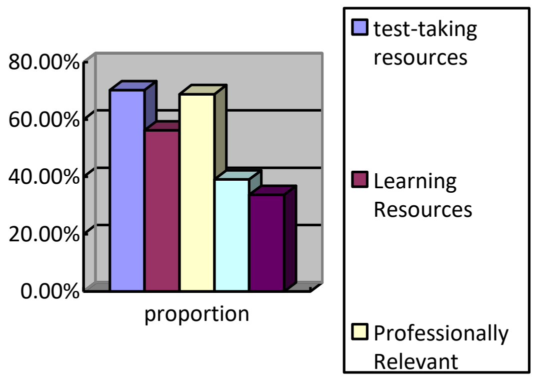

Figure 7: Types of English mobile learning resource requirements for vocational college students.

4.4 Resource presentation form

The image big data processing of the sample data shows that the students are more visual learners, and for the online learning resources of English, the form data presented is also more consistent. More students gravitate to the multiple resource formats of video, while audio and interactive methods are relatively unpopular (Figure 8).

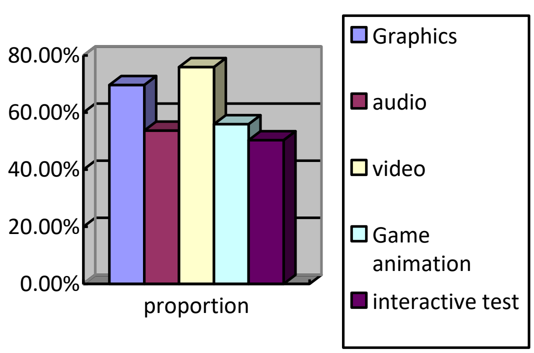

Figure 8: Presentation form preference of vocational college students' english mobile learning resources.

4.4 Personalized resource push research fits the development trend of information technology

In the specific development process, how to integrate the corresponding technology and teaching, promote the comprehensive development of students, solve the key and difficult problems in the process of various teaching development, motivate the universalization and fairness of education, and improve the effective and steady improvement of quality of education. By constructing the personalized push of corresponding learning resources, the personalized and self-organized development of online learning resources can be realized, the self-cognition of students can be maximized, and the development trend and future requirements can be kept up [21-23].

The abundance of online learning resources limits the energy of individual students, making it impossible for them to browse, learn, and explore them all. As a result, while individualized learning materials might save time and money, their availability may be limited. As a result, it is required to conduct assessment and analysis based on particular indicators, enhance specific indicators for evaluation, promote the efficient use of learning resources, and encourage the enhancement of college students' learning levels [24].

4.5 System push and customization should be adjusted dynamically centring on the learners

For online learning resources, digital learning resources mainly push online resources of interest to specific users from the perspective of learners, such as learning interest, cognitive level, and specific learning preferences. During the actual process of push, it is necessary to take the learner as the specific center and make dynamic push adjustments according to the feedback information of the learner, to achieve the satisfaction of the specific learner. Taken together, personalized push needs to include the following types of functions [25-26]:

- ❖ Analysis of Learners

The personalized push system actively pushes information resources that are of interest to users or that suit their needs according to the user's interests, hobbies or professional characteristics, and other personalized characteristics.

- ❖ Self-update of user interest model

College students' demand for digital learning resources has dynamic characteristics in terms of resource content and type.

- ❖ Behavior records

The personalized push system is an implicit score that can only be obtained by analyzing the online behavior of college students.

- ❖ Toolset and Demand Judgment

The personalized push system should provide a complete set of tools to predict the list of digital learning resources that college students are interested in based on recommendation algorithms.

4.6 Statistical analysis using ANOVA test

Analyzing the variations Among the acoustic response of the faulty samples and the pristine sample was necessary to assess our hypothesis. Analysis of variance (ANOVA) was the statistical method. At a confidence interval level, the second stage is to expand English knowledge outside the classroom, thus indicating that students even more expect to acquire knowledge of English outside the curriculum specified for ANOVA test input circumstances. An ANOVA test analyzes if information from multiple instances of a variable shares a similar mean. In essence, the ANOVA test can determine if various groups of an independent variable have distinct impacts on the reaction variable. ANOVA may be formally described as a linear model with multiple input sets and i answers per group, as shown in Equation (18).

$$x_{ji} = \in_i + \emptyset_{ji} \tag{18}$$

Here, z_{ji} is the response of the jth value are group of English language the mean group was calculated and Errors at random with a mean of zero and fixed values. y. The ANOVA test total variance of the number was calculated. To test for a variance in the group's in equation, divide the results into the subsequent two parts: (19).

$$\sum j \sum i \left(z_{ji} - y\right)^2 = \sum j\,(n) + \sum j\,(z_{ji} - z_j)^2 \tag{19}$$

Difference group of means from the overall mean, $z_{ji} - y^2$ variation among roupings wherein y is the overall mean of each group j and z is the overall sample mean.

The disparity between each group's observations and the group mean estimations of variation within a skill process group. Here n is the sample size of jth value where i=1,2,…N. An ANOVA test is used to compare the variation among the groups of variation within the groups. The ratio within the group significantly high outcomes in low values of k number of measures test analysis ($k - \mathrm{N}$, $N - 1$) degrees of freedom as presented in Equation (20).

$$F = \frac{\sum j \sum i \left(z_{ji} - y\right)^2 N-1}{\sum n_j \left(z_{ji} - y\right)^2 K-N} \tag{20}$$

The sample tests were conducted to compare the Acoustic reaction of the actuation amongst the harmed specimens. pristine position, then learning tests were analyzed and teachers in schools generally publish corresponding course resources through information-based teaching methods.

5 Discussion

Artificial intelligence teaching systems are contingent on technological infrastructure, potentially posing challenges in resource-constrained environments, and the success of the personalized learning platform heavily relies on its effectiveness and sensitivity. These are the limitations of the related works. Comparing our results to the related work limitations, our results provide better performance and efficiency.

6 Conclusions

With the development of the social economy, effective access to online learning resources has become increasingly important. Given these needs and deficiencies, based on image big data processing technology, this paper sorts out the business logic of personalized learning resource push, uses the time decay function to evaluate the transfer of learning interest points, and realizes the matching of cognitive level and learning difficulty according to the application difficulty. The service of personalized online resources is optimized to improve the efficiency of learning resources. The simulation experiment results show that the image big data processing technology is effective and can support the push evaluation of personalized learning resources. Limited generalizability due to specific image data requirements, potential resource constraints, and reliance on advanced technology infrastructure. For future research, explore real-world applications, integrate AI advancements, and enhance adaptability for dynamic curriculum changes in the personalized learning resource push.

Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of interest

The authors declare no conflicts of interest

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