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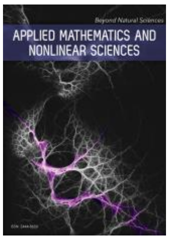

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Current Situation and Practical Path of Cultivating Students' Core Literacy in the Context of the New Era

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Abstract

In this paper, Bayesian estimation and Coleman filtering are used to compose a multidimensional data fusion algorithm to study the cultivation of students' personalized core literacy. A Trans E model is constructed based on the calculation of students' specific course ratings using collaborative filtering algorithms. Combining the knowledge graph and collaborative filtering methods, the similarities between the course and user ratings are calculated respectively. The user's rating situation can be predicted by combining similarity. Through the empirical analysis method, the overall and specific competency dimensions of students' core literacy and the effect of core literacy cultivation, as well as students' satisfaction, were analyzed, and the corresponding practice paths were proposed based on the analysis results. The mean value of students' core literacy test is 46.25, and the number of students scoring between 50-60 points is the largest, but the number of excellent students is 0, which is poor in the cultivation of core literacy. The analysis of the effect of core literacy cultivation shows that in the correlation analysis of teaching effect and teaching support, the p-value is less than 0.01, but most of the correlation coefficients are less than 0.35, and there exists a weak relationship between the two, and the school authorities should strengthen the teaching support of core literacy.

Keywords: Bayesian estimation; Coleman filtering; Multidimensional data fusion; Collaborative filtering; Trans E modeling.
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1 Introduction

Core literacy refers to the character and key abilities of students that can adapt to the lifelong development of individuals and social development, reflecting the concept of “virtue and talent” since ancient times [1-2]. Colleges and universities must pay great attention to the requirements of social and economic development on the quality and ability of graduates, targeted training of students’ core qualities, to achieve moral and technical training, multi-specialty, comprehensive quality, to better serve the development of the local economy [3-5].

With China’s education reform, it was officially proposed in 2014 to cultivate the core literacy of students at all stages [6]. In addition, the significance of cultivating core literacy lies not only in the “cultivation of the body”, i.e., the long-term development of the students themselves, but also, more importantly, the ability to promote the harmonious development of society [7]. Therefore, cultivating students’ core literacy is an imperative decision, a trend of education reform, and the focus of educators.

Yang, Z et al. classified students’ core literacy into three types: reading literacy, scientific literacy and mathematical literacy. The essential attributes and values of core literacy, i.e., the balance between the transmission of knowledge and the cultivation of literacy, and at the same time, need to pay attention to the transmission of the key knowledge of the discipline [8]. Liu, H and Ma, N analyzed and evaluated the core literacy of soccer science in China by using the technology of big data and the Internet of Things, and they believe that the level of core literacy development in soccer can, to a certain extent, reflect a country’s overall physical literacy and overall competitive level [9]. Zhao, Y believes that the core quality of higher art education lies in grasping the correct value orientation of art teaching, and colleges and universities should focus on the internalization of students’ knowledge and skills and improve students’ core quality of beauty and essence, which has a positive role in reshaping the sense of national cultural identity and passing on traditional culture [10].

Li, Y et al. proposed the 4C talent cultivation standard for the cultivation of core qualities in higher education, and this model adapted the teaching content and teaching methods to improve students’ life habits of cultivating body and health, learning attitude of diligence learning and skillful skills, and the pursuit of upward and good life [11]. Huang, D and Hoon-Yang, introduced deep learning algorithms combined with artificial intelligence and AR technology. Applied in the cultivation of core qualities of youth, their proposed method has a significant enhancement effect in terms of various dimensions, such as learning attitude [12]. Amaele, S found that examination malpractices are increasing and reported at all levels of the education system, and the main reason for this is the difficulty in the promotion of quality education. Hence, he argued that all levels of the education system should focus on quality education as an indisputable necessity to address the ills of formal schools [13].

This paper combines multidimensional data fusion and non-probabilistic fusion algorithms to study personalized core quality cultivation. Ontology-based contextual modeling reveals the core knowledge cultivation recommendation method. Using knowledge mapping tools, a model of literacy cultivation is constructed, and a traditional recommendation algorithm is used to evaluate the user’s scores on related courses, providing a basis for calculating the similarity between courses. The learning algorithm Trans E model is utilized to change the course entity model into a low-dimensional vector, and the maximum interval loss function between positive and negative samples is used as a training model for the knowledge graph representation results. Relevant data from the core literacy cultivation platform were collected, and the similarity between the courses was calculated through the scoring matrix, fused according to the proportion, and predicted the students' scores. Based on data fusion, the status quo of students' core literacy cultivation is empirically examined, and corresponding solution paths are proposed to address the problems existing in this status quo.

2 Personalized core literacy cultivation based on multi-dimensional data integration

2.1 Multidimensional data fusion

Data fusion organically blends old and new techniques, and probabilistic and mathematical-statistical methods are typically used by researchers in data fusion techniques. Generally, multidimensional data fusion methods can be categorized into probability-based methods and non-probability-based methods. Also, it can be divided into deterministic and non-deterministic theories. This paper divides the methods of multidimensional data fusion according to probabilistic methods.

2.1.1 Multidimensional data fusion algorithms

1) Bayesian estimation

Fusion of multidimensional data can be done using Bayesian estimation. When fusing, the data should be as independent as possible. By dividing independently, the system can be evaluated for decision-making using Bayesian estimation.

Assume that the decision that can be made in the system is $A1, A2, \cdots, Am$ and the observation is represented as B. This allows the use of emergent prior knowledge, which leads to the probability of making a decision $p(Ai)$ as well as the outcome that occurs under a certain decision $p(B \mid Ai)$. In Bayesian formulas, the probability of the outcome under the probability of the decision $p(B \mid Ai)$ can be transformed into the posterior probability $p(Ai \mid B)$. This allows for the use of conditional formulas for the representation of Bayesian formulas:

$$p(Ai \mid B \cap C) = \frac{p(B \cap C \mid Ai)p(Ai)}{\sum_{j=1}^{m} p(B \cap C \mid Ai)p(Ai)} \tag{1}$$

Where B is the observation and C is the observation under another source. For decision condition Ai, the probability of occurrence of observation C is $p(C \mid Ai) > 0$ such that the probability of simultaneous occurrence of B and C needs to be computed $p(B \cap C \mid Ai)$. However, this computation is difficult, so the formula can be further modified. First assume that A, B, C are independent of each other, i.e.:

$$p(B \cap C \mid Ai) = p(B \mid Ai)p(C \mid Ai) \tag{2}$$

Then the formula is rewritten as:

$$p(Ai \mid B \cap C) = \frac{p(B \cap C \mid Ai)p(Ai)}{\sum_{j=1}^{m} p(B \mid Ai)p(C \mid Ai)p(Ai)} \tag{3}$$

2) Kalman filtering

Kalman filtering is a method of feedback control for the state of a system process. The system has a certain state at a certain point in time, and these states are recorded and updated in the form of feedback to the entire system. In this way, the Kalman filtering system can be divided into two processes: the process of updating the state and the measurement of the updating process. The main operations performed during this updating process include the estimation of the current state and the calculation of the variance matrix of the error. The update equation can be measured using probability.

2.1.2 Non-probabilistic based fusion methods

The D-S theory, also known as the theory of evidence, was first proposed by Dempster and then expanded upon by Shafer. Uncertainty often exists in the real world, and this uncertainty is caused by the inability to know the cause. Therefore, a trust function can be used to measure this uncertainty, and a probability constraint is used to restrict the trust function, which ensures the availability of probabilities and prevents the inability to predict facts due to the unavailability of precise probabilities.

Let U be the recognition frame and $m:2^U \to [0,1]$ be the basic probability assignment on U. Define the function BEL:

$$BEL(A) = \sum m(B) \quad \forall A \subset Y \tag{4}$$

Is called the function is a trust function on U. $BEL(A)$ denotes the sum of the likelihood measures of all subsets of A, i.e., it denotes the total trust in A.

2.2 Recommended Methods for Core Quality Development Knowledge

Ontology-based context modeling can reveal information and the relationships between it more accurately. Ontology-based models mainly include the generalized user ontology model, unified user context model, and ontology-based user model, which are increasingly used in the fields of e-commerce, information recommendation, tourism, and mobile libraries. The ontology-based recommendation should semantically describe the recommended resources, use the similarity formula to calculate the similarity between the resources and use the ontology's inference rules to reason out the similar resources recommended to the user. Ontology-based knowledge recommendation can effectively solve the problems of cold start and matrix sparsity in recommender systems. Ontology-based knowledge recommendation requires the creation of a domain ontology to describe the recommended knowledge, which is the basis of the recommendation. The method of ontology-based semantic description is to describe the knowledge resources in an ontology language such as OWL so that the users and resources have semantic information, combined with collaborative filtering algorithms to calculate the similarity of the resources or users so as to improve the accuracy of the recommendation. Recommendation based on ontology rules is based on pre-set rules of reasoning so as to discover the knowledge resource correlation and recommend the knowledge with a higher degree of correlation to the user. The calculation of knowledge similarity is a requirement for all recommendations. In ontology networks, there are usually methods such as distance-based similarity calculation, content-based similarity calculation, and attribute-based similarity calculation. Among them, distance-based semantic similarity calculation is to calculate the number of directed edges with the shortest distance in the same network hierarchy, and in this calculation method, all directed edges have the same weight. The specific calculation formula is as follows:

$$sim\left(w_1, w_2\right) = \frac{2\times(MaxLenth-1)-\min\left(w_1, w_2\right)}{2\times(MaxLenth-1)} \tag{5}$$

The distance based semantic similarity formula is shown below:

$$D\left(W_1, W_2\right) = D_{\min}\left[W_1, Anc\left(W_1, W_2\right)\right] + D_{\min}\left[W_2, Anc\left(W_1, W_2\right)\right] \tag{6}$$

$$sim\left(w_1, w_2\right) = -\log\frac{1+D\left(w_1, w_2\right)}{d_{\max}} \tag{7}$$

Where $Anc\left(W_1, W_2\right)$ is the nearest common ancestor node of concept nodes w_1 and w_2 in the hierarchical network, $D_{\min}$ is the shortest distance of a concept node in the hierarchical network, and $d_{\max}$ is the maximum depth of the network.

The content-based semantic similarity calculation method is to calculate the amount of information of the common ancestor between two similar child nodes. This calculation method is derived from the concept of entropy in information theory. Its calculation formula is as follows:

$$IC(w) = -\log[P(w)] \tag{8}$$

$$P(w) = \frac{\text{Number of occurrences of concept } w \text{ in the training set}}{\text{Total number of training sets}} \tag{9}$$

The similarity obtained in this way is calculated as:

$$sim\left(w_1, w_2\right) = \frac{2\times IC\left[AnC\left(w_1, w_2\right)\right]}{IC\left(w_1\right)+IC\left(w_2\right)} \tag{10}$$

The attribute-based approach for computing the semantic similarity of concepts is shown below:

$$sim\left(w_1, w_2\right) = \theta f\left(w_1 \cap w_2\right) - \alpha f\left(w_1 - w_2\right) - \beta f\left(w_2 - w_1\right) \tag{11}$$

Let concepts w_1 and w_2 each have n attributes with attribute value $A_{k,w_1} = A_{0,w_1}, A_{1,w_1}, \ldots A_{n,w_1}$, $A_{k,w_2} = A_{0,w_2}, A_{1,w_2}, \ldots A_{n,w_2}$:

$$D\left(w_1, w_2\right) = \sqrt{\sum_{k=0}^{n}\left(A_{k,w_1} - A_{k,w_2}\right)^2} \tag{12}$$

$$sim\left(w_1, w_2\right) = \frac{\alpha}{\alpha + D\left(w_1, w_2\right)} \tag{13}$$

α as a moderator.

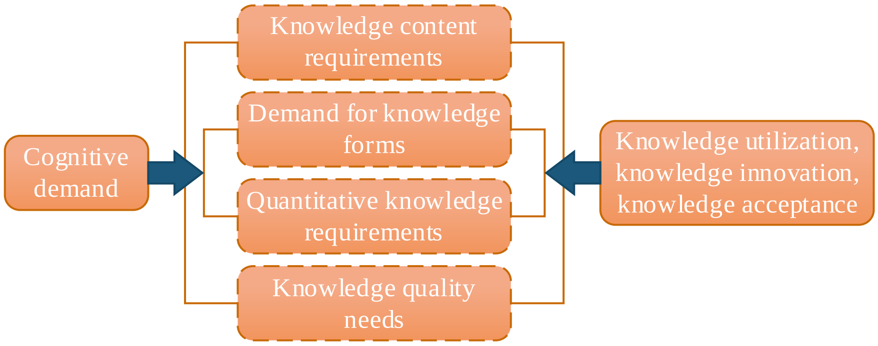

Figure 1. Type of the user's cognitive needs

Students' core literacy cognitive needs can be divided into four aspects: knowledge content needs, knowledge form needs, knowledge quantity needs, and knowledge quality needs, Figure 1 shows the types of user cognitive needs.

1) Knowledge content needs. Knowledge content includes knowledge in various fields, such as economics, management and other fields. It may also involve knowledge topics, and the knowledge provided through the virtual knowledge community can help users solve knowledge needs and fill the knowledge deficit state.

2) Knowledge from demand. In order to make it easier for users to acquire knowledge and understand the content of knowledge, the demand for knowledge forms arises. Knowledge form is the carrier of knowledge presentation, mainly including text form, image format and multimedia format. With the use of mobile terminals, audio and video formats are more likely to attract users' attention in the form of knowledge.

3) Knowledge quantity demand. The user's demand for knowledge is also expressed in the user's demand for the quantity of knowledge. The amount of knowledge demanded depends on the user's own experience, and there is no direct quantitative standard. The standard for the amount of knowledge is often the principle of moderation. The amount of knowledge can not be too much. Otherwise, it will lead to the phenomenon of knowledge overload, aggravating the cognitive burden on the user. The amount of knowledge should not be too little. Too little knowledge can not guide the user to practice to meet the user's knowledge needs.

4) Knowledge quality needs. Knowledge content is the intrinsic form of knowledge and ultimately determines the usefulness of knowledge in knowledge content.

3 Knowledge mapping-based knowledge module for literacy development

3.1 Traditional Recommendation Algorithms

In this paper, we use a collaborative filtering algorithm based on items for recommendation. The item-based collaborative filtering algorithm calculates the similarity between courses by looking at how users have rated specific courses.

The assumption of the item-based collaborative filtering algorithm is that user A and B give similar ratings for n item or user A and user B have similar behaviors, then they will give similar ratings or behaviors for other items. The entire recommendation process of the item-based collaborative filtering algorithm can be formally represented as a matrix of ratings with dimension $m \times n$ users and items $R_{m \times n}$:

$$R_{m \times n} = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1j} & \cdots & R_{1n} \\ R_{21} & R_{22} & \cdots & R_{2j} & \cdots & R_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ R_{i1} & R_{i2} & \cdots & R_{ij} & \cdots & R_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ R_{m1} & R_{m2} & \cdots & R_{mj} & \cdots & R_{mn} \end{bmatrix} \tag{14}$$

where R_{ij} represents the rating of item j by user i. Ratings of items are categorized into salient and implicit rating feedback. The explicit feedback is the evaluation and preference information provided by the user, and the accuracy of the information is directly related to the information provided by the user. Implicit feedback means that the system automatically builds models and predicts user preferences based on information about the user's usage history.

Content-based recommendations from the learner's interaction items recommend the use of learning resources that are similar to the learner's learning resource interaction items. The method first collects the user's behavioral characteristics, then finds the accessed content in the database, performs data mining on the searched behaviors and browsed content to get a typical vector, and then uses this vector and the related resources in the database to compare the similarity, and finally selects the closest one, Fig. 2 shows the principle of the content-based recommendation.

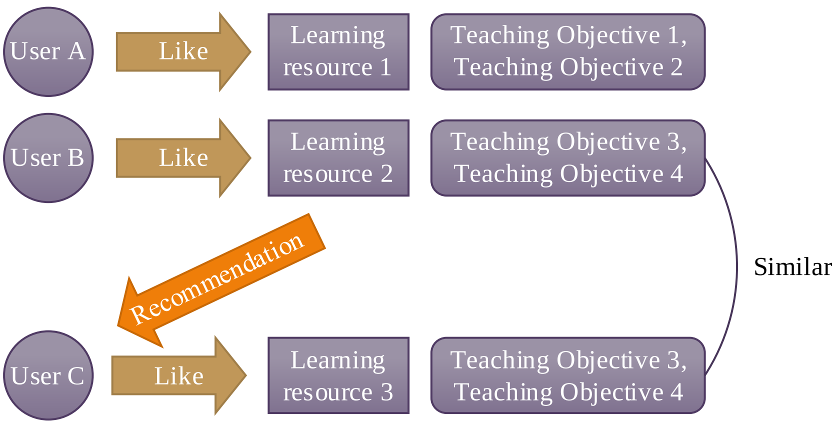

Figure 2. Content-based recommendation principle

3.2 Representation learning model construction

Trans E model is a typical algorithm and technical foundation model for early knowledge graph representation learning after the proposed knowledge representation learning algorithms such as Trans R, Trans H, and CKE-Trans R are evolved based on the idea of Trans E algorithm.

A ternary is represented by three different forms of entity-relationship-attribute (h,r,t), where entity (h) partially represents the head entity in the ternary, while relationship (r) represents the relationship in the ternary, and attribute (t) represents the head entity in the ternary. The entities and relations are then represented as vectors in their respective spaces, which are computed iteratively to finally make the different entity vectors and relation vectors of the triad in the knowledge graph satisfy the condition $h+r\approx t$ as shown in the Tran E model. If the triad is correct, then the value of $h+r$ will be infinitely close to the value of t, which is seen as a positive sample training. Conversely, if the value of $h+r$ is not close to the value of t, then the triad is wrong and is considered as negative sample training. To make the positive and negative training easy to distinguish out. The degree of closeness between $h+r$ and t can be measured in terms of vector similarity. The Trans E algorithm uses Euclidean distance to compute the similarity of two vectors, and Trans E's ternary score formula is defined as:

$$f(h,r,t)=\|h+r-t\|_{L_1/L_2} \tag{15}$$

The value of the score formula is as small as possible for positive sample triples and conversely as large as possible for negative samples. The Trans E model employs a loss function with the maximum interval between positive and negative samples to train to get the representation learning result of the knowledge graph. The loss function is defined as:

$$L=\sum_{(h,r,t)\in S}\sum_{(h',r',t')\in S'}\left[\gamma+f(h,r,t)-f\left(h',r',t'\right)\right]_+ \tag{16}$$

Where S denotes the data set of positive samples and S' denotes the data set of negative samples. The negative samples of the triad are derived by randomly replacing entity (h) and relation (r) during the continuous training process. $[x]+$ denotes $\max(0,x)$. r denotes the interval in the loss function, which is a hyperparameter greater than 0 that needs to be set. The loss function is minimized by a gradient optimization algorithm to optimally solve for the training objective of the Trans E model.

3.3 Course similarity calculation

3.3.1 Knowledge graph-based course similarity calculation

The course entities and relationships in the knowledge graph are represented as vectors in a low-dimensional space using the learning algorithm Trans E model, and the calculated distances between the resulting vectors are used to represent the degree of similarity between courses.

Each course entity and relationship is first mapped to a vector in a lower dimensional space, for example, course I_i is represented as a vector in the d nd dimension as $I_i=\left(E_{1i},E_{2i},\dots,E_{di}\right)^T$. Where E is the real value of course I in a d dimensional vector space.

After calculating the resulting similarity between the two courses, we find that the smaller the distance between the two vectors the higher the similarity between the two courses. Since the Euclidean distance was used to calculate the objective function in the Trans E model above, the Euclidean distance is also used here to calculate the course similarity:

$$d\left(I_i,I_j\right)=\sqrt{\sum_{k=1}^{d}\left(E_{ki}-E_{kj}\right)^2} \tag{17}$$

Where d represents the vector distance between course I_i and course I_j, if the value of d is smaller this means that the similarity between course I_i and course I_j is higher. In order to standardize the calculation the range of values of d is converted to greater than 0 and less than or equal to 1. The similarity between two courses is redefined as:

$$sim\left(I_i, I_j\right) = \frac{1}{1+d\left(I_i, I_j\right)} = \frac{1}{1+\sqrt{\sum_{k=1}^{d}\left(E_{ki}-E_{kj}\right)^2}} \tag{18}$$

3.3.2 Collaborative Filtering Based User Rating Similarity Calculation

Since the courses included in the Information Literacy Knowledge Atlas are from the Information Literacy Online Education Platform (ILOEP), the data analysis function of the ILOEP makes it possible to obtain information about the user ratings of the site:

$$sim\left(I_i, I_j\right) = \cos\left(S_i, S_j\right) = \frac{S_i \cdot S_j}{\left\|S_i\right\| \cdot \left\|S_j\right\|} = \frac{\sum S_{u,i} \cdot S_{u,j}}{\sqrt{\sum S_{u,i}^2} \cdot \sqrt{\sum S_{u,j}^2}} \tag{19}$$

In the actual learning process rating, different users have different personal guidelines for rating the same course, and different users have different heights for rating. So it is necessary to further improve the authenticity and accuracy of the ratings by correcting the cosine similarity formula and adding the average of the users' ratings to compare with this rating. Improved cosine similarity formula:

$$sim\left(I_i, I_j\right) = \frac{\sum_{U_{i,j}}\left(S_{u,i}-\bar{S}_u\right)\cdot\left(S_{u,j}-\bar{S}_u\right)}{\sqrt{\sum_{U_i}\left(S_{u,i}-\bar{S}_u\right)^2} \cdot \sqrt{\sum_{U_j}\left(S_{u,j}-\bar{S}_u\right)^2}} \tag{20}$$

Where $\bar{S}_u$ represents the average of the user ratings. This reduces the problem of inconsistent user rating guidelines.

3.3.3 Similarity Fusion and Predicting User Ratings

Firstly, the ternaries in the information literacy knowledge graph are represented and learned through the Trans E model, and then the resulting vector representations are computed to derive the results of course similarity based on the knowledge graph, and then the user ratings collected from the online education platform, the user ratings matrix is computed to calculate the similarity between the courses, and the two similarities are fused according to a certain ratio. The fusion formula:

$$sim\left(I_i, I_j\right) = \alpha \cdot sim_1\left(I_i, I_j\right) + (1-\alpha) sim_2\left(I_i, I_j\right) \tag{21}$$

Rating prediction is the introduction of the similarity between courses in the knowledge graph can predict the user's rating for the items that did not produce interaction records, thus generating a recommendation list. P_{ui} represents the result of rating prediction of user u for course i. The formula for P_{ui}:

$$P_{ui}=\frac{\sum sim\left(I_i,I_j\right)\times S_{u,j}}{\sum sim\left(I_i,I_j\right)} \tag{22}$$

Where $sim\left(I_i,I_j\right)$ represents the similarity between course I_i and course I_j.

4 . Cultivation of Students' Core Literacy and Practical Paths

4.1 Analysis of the current situation of the development of core qualities of data integration students

4.1.1 Overall analysis of student core literacy levels

Two hundred and eighty-five valid test papers were obtained, and the performance of these valid test papers, to some extent, can reflect the overall level of core literacy of high school students in N secondary schools, as well as the level of core literacy of high school students in N key high schools from the side. Based on the students' performance in the test papers were categorized and analyzed from the following three dimensions of ability, which are learning comprehension ability, practical application ability and innovative transfer ability. Then the students' core literacy level was analyzed objectively through summarization.

After the test paper was organized, the data analysis of the student's answers to the test paper was carried out to obtain the histogram of the distribution of the total score of the student's performance. Figure 3 shows the distribution of the performance, which can be learned through the following figure that the students' performance roughly conforms to the normal distribution, with a mean value of 46.25, and the students' performance reaches the largest share of the number of people between 50-60 points, with 225 people, accounting for 78.95% of the number of valid test papers. However, the total score of this test paper is 72, and if 43.2 is considered as the passing score, then the number of students achieving 43.2 and above in this test is 191, which is 67% of the number of valid test papers. Therefore, from the results of this graph, the number of passing is almost more than the total number of general, according to the 61 points for the excellent score, then the number of people who reached the excellent is 0, which indicates that the level of core literacy of the students in this school is generally low, and this aspect of the student's literacy needs to be strengthened to cultivate, which needs to be paid attention to by all educators. This indicates that the gap between the scores of the respondents of this survey is relatively large, and the school needs to pay enough attention to it and should strengthen its understanding of the student's learning situation and, if necessary, analyze the learning situation.

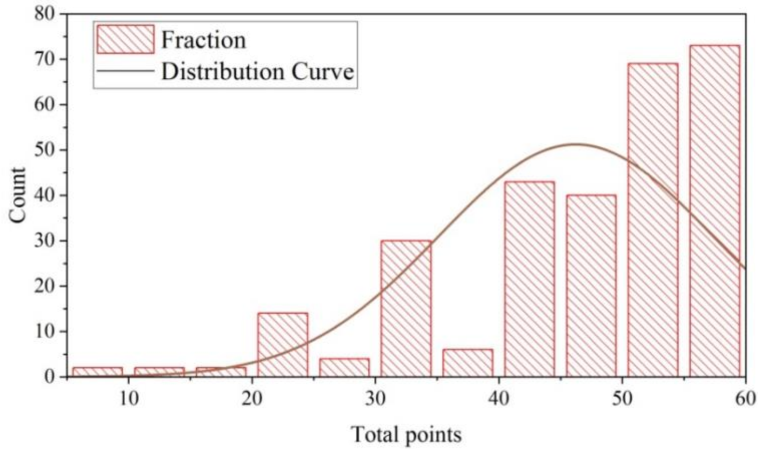

Figure 3. Performance distribution

4.1.2 Core Literacy Competency Dimension Analysis

Figure 4 shows the performance of the tested students on the dimensions of L2 competence. As can be seen from the figure, learning comprehension has the highest scores, where observational memorization scores are lower than those of generalization and comprehension, and simple problem-solving is instead the highest.1, 2, and 3 examined the memorization of knowledge, comprehension and generalization, and illustrative examples, respectively in general terms.

The scores of the three competencies were ranked as learning and understanding > practical application > creative transfer and the mean values of the scores were 0.8367, 0.6367, and 0.29, respectively.

By analyzing and understanding the questions and scores, it is believed that the content of the core literacy knowledge of the students under the test is vague, and many of them can’t remember the meaning of the knowledge points at all. Despite this, the majority of the students were capable of comprehending and summarizing the knowledge points. The third question had the highest score, and it was learned through interviews with students that the amount of training in this area was higher, so they were still more comfortable with this area. The scoring rate of analyzing and calculating ability and simple problem-solving in practical application ability is higher than that of inferring and explaining ability, which shows that the students’ inference and conjecture ability is relatively weak, and we learned through the author’s interviews that there is a small amount of training in this area of the topic of inference and conjecture and the exposure is relatively small, so the understanding of this area is relatively lacking, and this is also related to practical hands-on ability in real life. According to the scoring rate of the secondary ability indicator in the dimension of creative transfer ability, it can be found that almost all students have not reached this ability, which requires more attention from teachers, students and parents.

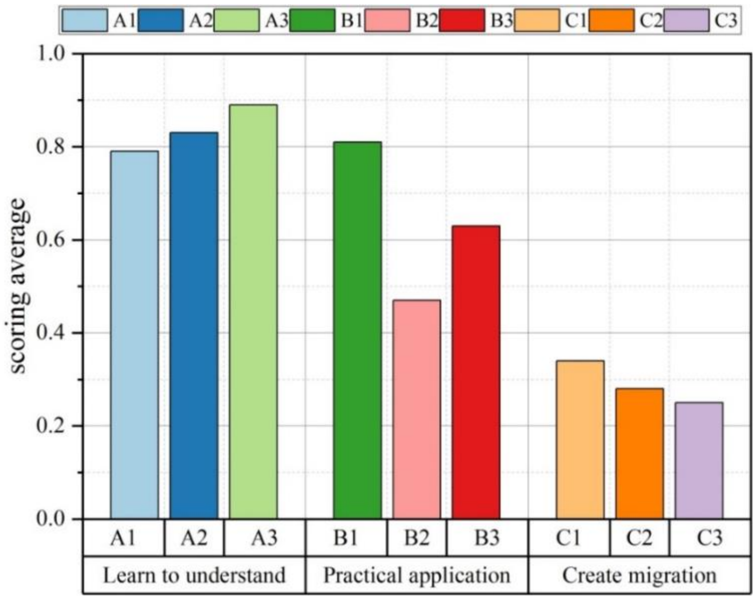

Figure 4. Students' performance in the secondary competence dimension

4.2 Analysis of the effect of cultivating students' core qualities

4.2.1 Analysis of teaching effectiveness

Using the literacy cultivation method based on knowledge mapping proposed in this paper, the core literacy competencies of college students were cultivated for a period of 20 weeks. Table 1 shows the analysis of teaching effects after cultivation, and correlation analysis was utilized to go on to study the correlation between the teaching effects and the teaching support and the acronyms in the table represent six kinds of teaching effects, which are the improvement of professionalism, the reinforcement of professional competence, the mastery of professional knowledge, the in-depth clarification, Reasoning, and Judgment. Pearson's correlation coefficient was utilized to demonstrate the strength of the correlations. In the correlation analysis between teaching effectiveness and teaching support, the p-value is less than 0.01, which shows the significance between teaching effectiveness and teaching support, and all correlation coefficients are greater than 0.1, which indicates that the correlation is positive. From the values in the table, the majority of the values are less than 0.35, which indicates that the correlation between teaching effectiveness and instructional support is weak. In the correlation between teaching effectiveness and teaching support, the correlation coefficients between the six items of teaching effectiveness and the "unit teaching time" in teaching support are the largest, which are 0.3715, 0.3851, 0.3642, 0.2971, 0.3423, 0.2793, and the correlation coefficients of "in-depth clarification" and "in-depth clarification" are the largest, which are only The correlation coefficient between "in-depth clarification" and "teaching resources" is the largest, and the correlation coefficient between "specialized knowledge" and "teaching resources" is also large. The correlation coefficients between "in-depth clarification" and "teaching resources" are the largest, and "specialized knowledge mastery" and "teaching resources" are also larger, indicating that teaching resources and unit teaching time in teaching support have a greater impact on teaching effectiveness.

Table 1. Analysis of teaching effect

Pearson, Related-standard format							
Teaching support		PQI	PAS	MPK	TC	Inference	Judge
	Teaching materials	0.2963**	0.1893**	0.3042**	0.3043**	0.2813**	0.2146**
	Teaching experience	0.3563**	0.2963**	0.2641**	0.2246**	0.1925**	0.1735**
	Platform maintenance	0.2954**	0.1932**	0.2951**	0.2434**	0.2617**	0.2074**
	Platform design	0.2943**	0.1836**	0.2432**	0.1234**	0.2721**	0.2193**
	Time prompt	0.2956**	0.2854**	0.3063**	0.2441**	0.1863**	0.2559**
	Unit teaching time	0.3715**	0.3851**	0.3642**	0.2971**	0.3423**	0.2793**

4.2.2 Analysis of student satisfaction

Table 2 shows the analysis of learning satisfaction, in which (1)-(9) represent the dimensions of student satisfaction, which are face-to-face support, learning guidance, technical guidance, formulation of performance, form of instructional organization, design of instructional activities, collaborative atmosphere, collaborative peers, and collaborative effectiveness. In the correlations between student satisfaction and instructional support, the p-values were all >0.01, indicating that the correlations between student satisfaction and instructional support showed significance, and the correlation coefficients of each correlation were >0, which indicated that the correlations were positive. From the Pearson correlation coefficients, most of them are concentrated in the range of [0.3,0.4], indicating that the correlation between student satisfaction and instructional support is low. Among all the larger correlation coefficients, there is no regularity, indicating that the correlation between student satisfaction and instructional support indicators is relatively scattered and does not show a correlation that is more linked to a particular indicator.

Table 2. Learning satisfaction analysis

Pearson, Related-standard format						
Teaching support		(1)	(2)	(3)	(4)	/
	Teaching materials	0.3525**	0.3812**	0.3167**	0.3416**	/
	Teaching experience	0.3456**	0.3071**	0.3015**	0.3743**	/
	Platform maintenance	0.3321**	0.2614**	0.3214**	0.3362**	/
	Platform design	0.2641**	0.3914**	0.3147**	0.3452**	/
	Time prompt	0.3712**	0.3912**	0.3926**	0.4321**	/
	Unit teaching time	0.3601**	0.3715**	0.3321**	0.3753**	/
		(5)	(6)	(7)	(8)	(9)
	Teaching materials	0.2934**	0.3142**	0.3152**	0.3536**	0.3642**
	Teaching experience	0.3641**	0.3921**	0.2985**	0.3891**	0.3523**
	Platform maintenance	0.3647**	0.3251**	0.2894**	0.2954**	0.3485**
	Platform design	0.3715**	0.3483**	0.3345**	0.2922**	0.3214**
	Time prompt	0.4851**	0.2463**	0.321**	0.3095**	0.3069**
	Unit teaching time	0.3245**	0.3175**	0.3176**	0.3561**	0.3146**

4.3 Practice Path Analyzed

Aiming at the problems existing in the current situation of students' core literacy cultivation, this chapter proposes the following practical paths.

1) Advocating the curricular concept of higher-order learning and continuously improving the program of curriculum construction, learning is an important path to enhance academic challenge. Learning is a key path to cultivating higher-order cognitive literacy and social-emotional literacy.

2) Accelerate the promotion of teachers' role transformation and enhance the effectiveness of teaching practice. Classroom teaching is the main channel for talent cultivation, and teachers play a crucial role in talent cultivation.

3) Colleges and universities should uphold the concept of value co-creation, dig deeper into the effective path of cultivating students' core literacy, and form a mechanism for continuous improvement of talent cultivation quality.

5 Conclusion

This paper studies the cultivation of students' core literacy and the practice path in the context of the new era, analyzes the overall level of students' core literacy and the dimensions of various aspects of competence, derives the status quo of the cultivation of students' core literacy, and then puts forward the corresponding practice path in response to the status quo, and the following are the main work and conclusions of this paper:

1) Based on multidimensional data fusion and non-probabilistic fusion methods, the concept of students' personalized core literacy cultivation is proposed, and ontology-based context modeling reveals the way of core literacy knowledge recommendation.

2) Calculate the similarity of core literacy cultivation courses using a collaborative filtering algorithm, construct a representation learning model, and calculate the similarity of two vectors based on it using Euclidean distance.

3) Designing empirical analysis to analyze students' core literacy cultivation based on the perspective of data fusion, the mean value of students' performance distribution is 46.25, and the mean value of scoring rate on the three secondary competency dimensions of learning comprehension, practical application, and creativity transfer is 0.8367, 0.6367, and 0.29, respectively, which is at a low level.

4) In the student satisfaction test, the Pearson correlation coefficient of satisfaction ranges from 0.3 to 0.4, indicating that there is a low correlation between students' core literacy cultivation and satisfaction and that the current status of students' core literacy cultivation is poor in general. In view of the problems related to core literacy development, this paper proposes a practical approach for school authorities.

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