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An analytical study of shortest path algorithms for learning paths in French courses with digital resources

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ABSTRACT

Students have the problems of insufficient self-control, insufficient learning motivation and unplanned and unsystematic for independent learning of university French. In order to solve this problem effectively, this study proposes the reform of French blended education model guided by POA theory. In this paper, we design a hybrid intelligent teaching mode of university French guided by the output-oriented approach, improve it based on the mutation operation in the genetic algorithm, propose the adaptive mutation genetic algorithm, and optimize the BP neural network with this algorithm. The GA-BP neural network is trained through simulation experiments to verify the performance of the algorithm. Using SEM structural equation modeling, the measurement model of six dimensions, namely, learning effect, teaching effect, learning input, objective learning conditions, subjective learning factors and learning ability, is established, integrating factor analysis and path analysis, and relevant research hypotheses are proposed. The feasibility of the hypotheses is verified one by one through empirical research. The path coefficients between each variable in the model and the path coefficients of the factor loadings are all at the significant level of 0.000, and all of them are positive, the path coefficients' validity is within the acceptable range, and the hypotheses proposed in this paper are all supported. Compared with the default path, 69.78% of the students in the recommended path for learning French think that the knowledge of the recommended learning path is easy to understand, and the learning path constructed on the basis of the educational resources of the output-oriented method can better satisfy the learning needs of the students compared with the default learning path.

Keywords: output-oriented method, genetic algorithm, SEM structural equations, BP neural network, French course learning

1. Introduction

As a world language, French has an important international status. In today's context of globalization,

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learning French can not only provide more opportunities for personal career development, but also enhance the understanding of French culture and Francophone countries [1-4]. And in the context of digital resources, the analysis of the shortest path algorithm of the learning path of French courses is of great significance for learning French [5-6].

With the continuous progress of science and technology and the arrival of the digital era, the application of digital learning resources in various fields has become increasingly popular [7-9]. In the field of French language education, the use of digital learning resources also shows great potential and advantages. Digital learning resources provide a variety of learning resources, including images, audio, video and other multimedia teaching content [10-13]. Unlike traditional teaching materials, multimedia teaching resources can present more vivid and intuitive language knowledge and language use scenarios and examples to stimulate learners' interest and motivation [14-16]. Through watching videos and listening to audio, learners can better understand and master speech, intonation and language expression skills. In addition, multimedia teaching can also display grammar, vocabulary and other knowledge points in the form of images, pictures and other forms, providing a visual learning experience, so that learners can absorb and memorize the knowledge more easily [17-20].

Although digital learning resources bring many benefits in improving French language proficiency, they also face some challenges. First, the quality and credibility of the content of digital learning resources need to be ensured to avoid misleading or ineffective learning experiences for learners [21-24]. Second, the use of digital learning resources needs to be complemented by appropriate pedagogical guidance and assistance to help learners make better use of these resources for learning [25-26].

This paper identifies the types of teaching resources, establishes the screening criteria for teaching resources, and builds the framework of digital teaching resources. It improves the content construction of digital teaching resources for French courses from the aspects of teacher resources and course resources, and proposes a digital teaching resource base for French courses based on POA. Starting from the three stages of driving, enabling and evaluating, a hybrid intelligent education model of French based on the output-oriented method is designed. Adaptive mutation genetic algorithm is used to improve the BP neural network, and data samples are obtained through the algorithm. According to the idea of constructing the teaching resources evaluation index system, data samples are obtained and data preprocessing is carried out. SEM structural equation model is utilized to establish a measurement model, put forward the corresponding hypotheses, and integrate the factor analysis and the path analysis to evaluate the teaching effect of the output-oriented method. Design research experiments to test the hypothesized results through path analysis method and evaluate the learning effectiveness of French language through empirical survey method. Based on the results of the analysis, we propose strategies to improve French learning from the levels of students and teachers respectively.

2. Establishment of educational resources for the French language curriculum based on the output-oriented approach

2.1. *Pathways for building educational resources for French-language courses*

2.1.1. Systematic planning of digital teaching resources for French language courses. First of all, it is necessary to determine the type of teaching resources and build strict screening standards for teaching resources. The construction of digital teaching resources requires that the selected teaching resources reach a high quality and standard, so as to guarantee the support of teaching resources to the teaching process and teaching content, and realize the goal of cultivating high-quality talents.

Next is the framework construction of digital teaching resources. Teachers first carry out teaching assumptions from four aspects: output-driven, input-enabled, choice learning and evaluation for learning, and then complete teaching tasks and achieve teaching goals according to the interactive teaching process consisting of a number of cyclic chains of driving-enabling-evaluation.

2.1.2. Improving the content of digital teaching resources for French courses. First, the construction of teachers' resources. Teachers' resources are mainly the curriculum resources prepared and accumulated by the teachers of French courses in the process of teaching. Including text resources, image material resources, animation resources, microclasses, PPT courseware and so on.

The second is the content construction of boutique resources, which refers to the online course resources based on the Pan-Asia platform, Mucun.com and other platforms, including digital teaching resources such as media materials, network videos, network materials, and boutique open courses. The boutique resources are more in number and variety, and in more diverse forms, which are not only important auxiliary resources for students' independent learning, but also have a positive contribution to enriching teachers' teaching resources and improving their teaching ability.

2.1.3. Application of POA-based digital teaching resources for French courses. First, according to the core qualities of Chinese students' development and the teaching guide of French undergraduate majors, as well as the teaching process of POA, we build a framework of digital teaching resources for the French course, i.e., eight modules and three small boards. With teachers' resources and high-quality resources, we will improve the content construction of resources and build a platform of common construction, common governance and common sharing. Secondly, combined with the specialized French courses and teaching materials, the digital teaching resources of French courses are applied under the guidance of POA. Finally, based on the evaluation indexes of teaching materials of POA, the digital teaching resources of French courses are effectively evaluated to optimize the construction of resource library.

2.2. Design of a Hybrid Intelligent Educational Model for French Based on the Output-Oriented Approach

The blended intelligent teaching model of university French guided by the output-oriented approach refers to the support of intelligent teaching platforms such as Wisdom Tree and Learning Access, the organization of relevant teaching activities in accordance with the POA teaching process, and the assessment based on learning outputs in order to promote the effective implementation of blended French teaching [27].

2.2.1. Driving phase. The driving stage is the beginning of the teaching process. Before the lesson, the teacher creates specific communicative scenes and discussion topics through the intelligent teaching platform, and at the same time provides diversified input materials for students' independent and selective learning, and guides students to try to complete the output tasks. In the process of attempting, students will realize their own shortcomings in language and cultural accumulation, which will stimulate their enthusiasm for learning French and create a sense of urgency.

2.2.2. Enabling phase. The facilitation stage is a key stage in the teaching and learning process. In the classroom, teachers help students master language forms, contents and expressions through targeted teaching activities to accomplish tasks and enhance teaching effectiveness. Teachers should design creative and interesting activities according to students' knowledge base, cognitive level and learning characteristics, and mobilize students to participate actively. By participating in facilitation activities, students can improve their language skills. In the facilitation stage, the teacher plays the role of a facilitator and supporter, pushing students to complete the task successfully.

2.2.3. Evaluation phase. The evaluation stage is the final stage of the teaching and learning process. The core concept of this stage is to place students' output results at the heart of the learning process. In order to better evaluate the output results, cooperative teacher-student evaluation can be used in the form of student self-assessment, mutual evaluation and teacher evaluation, as well as online evaluation through the Learning Link platform. It mainly assesses students' oral and written output results to achieve the effect of assessment for learning. In the evaluation session, teachers need to provide effective feedback and assessment of students' outputs in order to improve the quality of students' outputs. At the same time, teachers also need to work with students to develop evaluation criteria and guide students to participate in the evaluation process to maximize the learning effect.

3. Study of the shortest path model for learning French courses

3.1. GA-BP Neural Network Modeling

3.1.1. Adaptive variational genetic algorithms. In this paper, the adaptive mutation genetic algorithm (GA) is proposed, which is an improvement of the mutation operation in genetic algorithms, which helps to improve the diversity of the genetic algorithm populations, and the mutation probability is currently derived from continuous experimentation [28].

In this paper the adaptive mutation probability P is calculated as shown in equation (1):

$$\begin{aligned} P &= \left(P_1 + P_2\right)/2 \\ &= \left(P_0 - \left(P_0 - P_{\min}\right) * m / M + P_0 * \max_{X_K \subset \Omega} F\left(X_K\right) / \bar{F}\right) / 2 \end{aligned} \tag{1}$$

where M is the maximum number of evolutionary generations, m is the current number of evolutionary generations, P_1 is inversely related to the number of evolutionary generations, P_2 is inversely related to the average fitness value, P_0 is the assumed initial probability of variation, $P_{\min}$ is the minimum of the range of values of the probability of variation, $\bar{F}$ is the average fitness value of the current population, and $\max_{X_i \subset \Omega} F\left(X_i\right)$ is the maximum fitness value of the current population.

3.1.2. GA-BP modeling. In this paper, adaptive mutation genetic algorithm is used to improve the BP neural network, i.e., adaptive mutation genetic algorithm optimized BP neural network model (GA-BP), which consists of two main parts, i.e., BP neural network part and adaptive mutation genetic algorithm part.

3.2. BP Neural Network Design

1) Determination of the number of network layers and nodes. A feedforward neural network with a single hidden layer is able to map all continuous functions, and two hidden layers are needed only when learning discontinuous functions, so a multilayer feedforward neural network needs at most two hidden layers [29]. When designing a multilayer feedforward neural network, in general, one hidden layer is considered first. If the number of nodes in the hidden layer is sufficiently large and the network performance does not improve, the training cost will increase along with it before considering increasing the number of hidden layers, so in this paper, we try to use one hidden layer first.

The input layer receives data from external inputs, so its number of nodes depends on the dimension of the input vector of the specific problem. The transfer function used in the input layer is generally linear, i.e. $f(x) = x$.

Trial-and-error method is one of the methods to determine the number of nodes in the implicit layer, which, after determining the initial value, can be used to conduct experiments by increasing the number from less to more, and analyze the optimal number through the results of the experiments. There are three forms of determining the initial value of the trial-and-error method, as shown in Eq.

(2) to Eq. (4), respectively, and in this paper, we use the empirical Eq. (2) to determine the initial number of nodes of the implied layer:

$$m=\sqrt{n+l}+a \tag{2}$$

$$m=\log 2^{n} \tag{3}$$

$$m=\sqrt{nl} \tag{4}$$

Where m is the number of nodes in the implicit layer, n is the number of nodes in the input layer, l is the number of nodes in the output layer, and a is a constant between 1 and 10.

The number of nodes in the output layer depends on the dimension of the target variable in the actual problem, using a nonlinear transfer function, the more commonly used nonlinear transfer function is the hyperbolic function equation (5):

$$f(x)=\frac{1}{1+e^{x}} \tag{5}$$

2) Determination of the number of samples. Obtain data samples, according to the idea of the construction of teaching resources evaluation index system, obtain data samples, data pre-processing. Generally speaking, the more experimental samples, the more accurate the results of the response, but when the number of its amount reaches a certain amount, the accuracy is fixed in a range, and will not change. the larger the size of the network, the network mapping relationship is more complex, in general, the number of training samples is the number of the total number of network connection weights of 5-10 times. Generally speaking, the number of training samples is 5-10 times of the total number of connected weights of the network.

3) Selection of initial weights. There are generally two ways to select the initial weights of the network: the first method is to take a small enough initial weights; the second method is to make the initial value of +1 and -1 weights are equal.

4) Learning rate. Learning rate is an important influence on the amount of change in the weights in the loop training, if the value is chosen large, it will lead to system instability; choose a smaller one will increase the training time, but it can ensure the error margin.

5) Determination of stopping conditions. There are two ways to stop the training, one is controlled by the error margin, and the other is to reach the maximum number of iterations, and the training can be stopped as long as one of the two conditions occurs. Usually, multiple networks can be trained and finally the appropriate network is selected based on the analysis results.

The neural network vector model with a single hidden layer used in this paper is represented in MATLAB as shown in Figure 1 below.

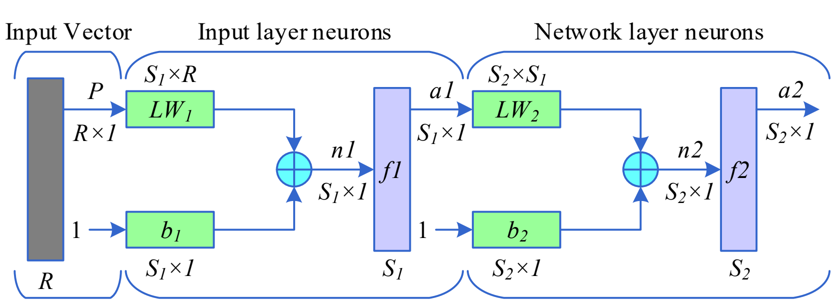


Fig. 1. The vector model of multi-layer neural networks in MATLAB

p is the input vector of the neural network with size $R\times 1$ as shown in equation (6):

$$p=\left[p_1,p_2,\cdots,p_R\right] \tag{6}$$

b_1 is the threshold vector of the input layer neuron with size $S_1 \times 1$, as shown in Equation (7):

$$b_1 = \left[b_{1,1}, b_{2,1}, \cdots, b_{s_{1,1}} \right] \tag{7}$$

IW_1 is the connection weight vector of the input layer neurons to the input vector with size $S_1 \times R$, as shown in Equation (8):

$$IW_1 = \begin{bmatrix} iw_{1,1}^{1,1} & iw_{1,2}^{1,1} & \cdots & iw_{1,R}^{1,1} \\ iw_{2,1}^{1,1} & iw_{2,2}^{1,1} & \cdots & iw_{2,R}^{1,1} \\ \cdots & \cdots & \cdots & \cdots \\ iw_{S_1,1}^{1,1} & iw_{s_1,2}^{1,1} & \cdots & iw_{s_1,R}^{1,1} \end{bmatrix} \tag{8}$$

$n1$ is the result of the intermediate computation of the first layer of neurons, i.e., the weighted sum of the connection weight vector and the threshold vector with a size of $S_1 \times 1$, as shown in Equation (9):

$$n1 = IW_1 p + b_1 \tag{9}$$

a_1 is the output vector of the first layer neuron with size $S_1 \times 1$ as shown in Eq. (10):

$$a1 = f1\left(IW_1 p + b_1 \right) \tag{10}$$

The description of the output layer's inter-weight values, output vectors, etc. will not be repeated here.

3.2.1. Basic steps of adaptive variational genetic algorithm:

1) Coding. Genetic algorithm in the process of solving the actual problem, not directly on the feasible solution search, but first of all on the feasible solution of the individual coding, coding mode to a greater extent affects the efficiency of the genetic algorithm to search for the global optimal solution [30]. The main coding methods of genetic algorithm include: binary coding, sequence coding, real number coding, tree coding, disordered coding, large character set coding and so on.

For example, the structure of a neural network is shown in Fig. 2, where W_{ij} is the weights and θ_n is the threshold. Its coding is: $\left(W_{11}, W_{12}, \theta_1, W_{21}, W_{22}, \theta_2, W_{13}, W_{23}, \theta_3 \right)$. The coding length is: $S = P * S_1 + S_1 * S_2 + S_1 + S_2$, where S_1 is the number of nodes in the implicit layer, S_2 is the number of nodes in the output layer, and P is the number of input evaluation indicators. The initial weights of the model in this paper are $18*5 + 5*1 = 95$, the inter-value is $5 + 1 = 6$ and the coding length is $95 + 6 = 101$.

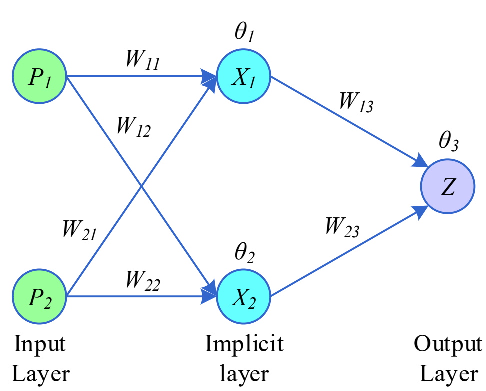


Fig. 2. A BPNN structure

2) Determination of initial population. The initial population is a collection of initial solutions, the

larger the number of individuals in the initial population, the greater the diversity of the initial population, and the greater the probability of searching for the global optimal solution. However, if the initial population size is too large, it will directly lead to more calculations of the fitness function, resulting in a reduction in the efficiency of the solution, so the initial population size should not be too large or too small.

3) Calculation of fitness. The search goal of the genetic algorithm is to obtain the network weights and thresholds that minimize the error sum of squares of the network in all evolutionary generations, while the genetic algorithm evolves in the direction of increasing the value of the fitness function, so the fitness function is set to be the inverse of the learning error of each individual. The learning error is shown in equation (11) and the fitness function is shown in equation (12):

$$E = \frac{\sum_{k=1}^{P}\sum_{j=1}^{l}\left(y_j^k - o_j^k\right)}{2} \tag{11}$$

$$fitness = \frac{1}{E} \tag{12}$$

Where E is the learning error, p is the number of training samples i.e. 900 sets of evaluation data, l is the number of output nodes 1, and $y_j^k - o_j^k$ denotes the error of the kth sample with respect to the jth output node.

4) Genetic operation. In this paper, the roulette wheel selection method, also known as proportional selection or replication, which first calculates the fitness value of a certain generation of individuals, i.e., the BP neural network weights and thresholds, and then calculates the proportion of this fitness value in the total fitness value, i.e., it is the probability of this individual to be selected in the selection process. The calculation of the selection probability is shown in Equation (13):

$$z\left(a_j\right) = \frac{f\left(a_j\right)}{\sum_{j=1}^{d} f\left(a_j\right)} \tag{13}$$

where a_j denotes an individual in the population, $z\left(a_j\right)$ is the probability of a_j being selected, $f\left(a_j\right)$ is the fitness value of the individual a_j, and d is the population size 20.

After calculating the probability of each individual being selected, it is necessary to determine whether this selected individual can continue to be inherited into the next generation of individuals based on the size of the accumulated probability. The calculation formula is shown in Equation (14):

$$q\left(a_k\right) = \sum_{j=1}^{k} z\left(a_j\right) \tag{14}$$

$q\left(a_k\right)$ is the accumulation probability of individual a_k, which in turn is genetically manipulated to obtain a new population of the next generation, determine the fitness value, and repeat the above steps until the population is stabilized.

3.2.2. Analysis of experimental results of GA-BP neural network modeling:

1) Training of GA-BP neural network [31]. Figure 3 shows the change of the optimal individual fitness, Figure 3 can be seen in the optimal fitness value before reaching convergence, after three times of decline, the first two were in the 2nd and 8th iteration, the optimal fitness declined rapidly, the 26th iteration fitness declined slightly, after that, convergence of the optimal fitness basically remained stable to reach the convergence state. It can be known that the optimal solution has been found after 26 iterations, after that the iteration process has little significance, and the change of the population is almost very small. 50 iterations are completed, the information of the best individual

that is the improved neural network weights and thresholds, and as the initial value of the model training, and began to use for the training of BP neural network.

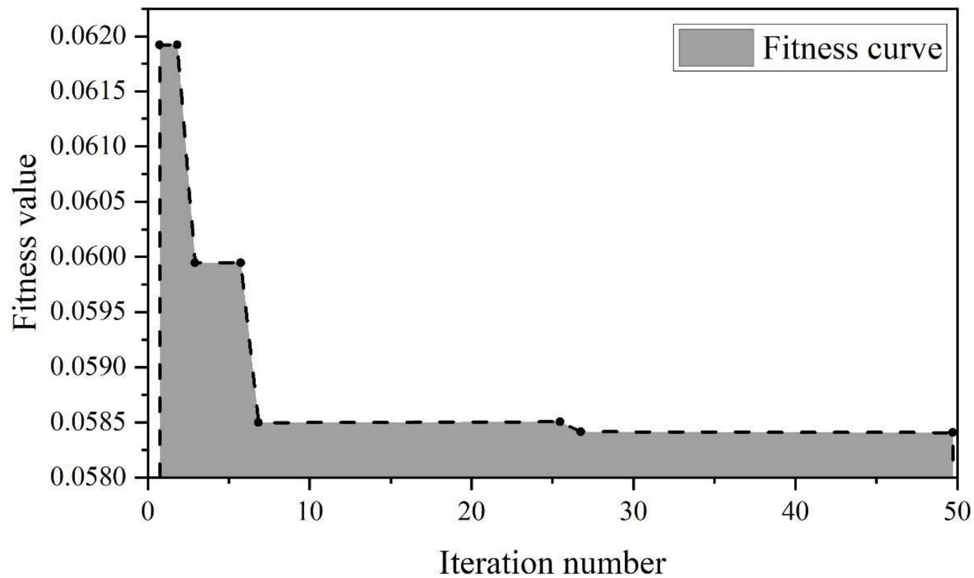
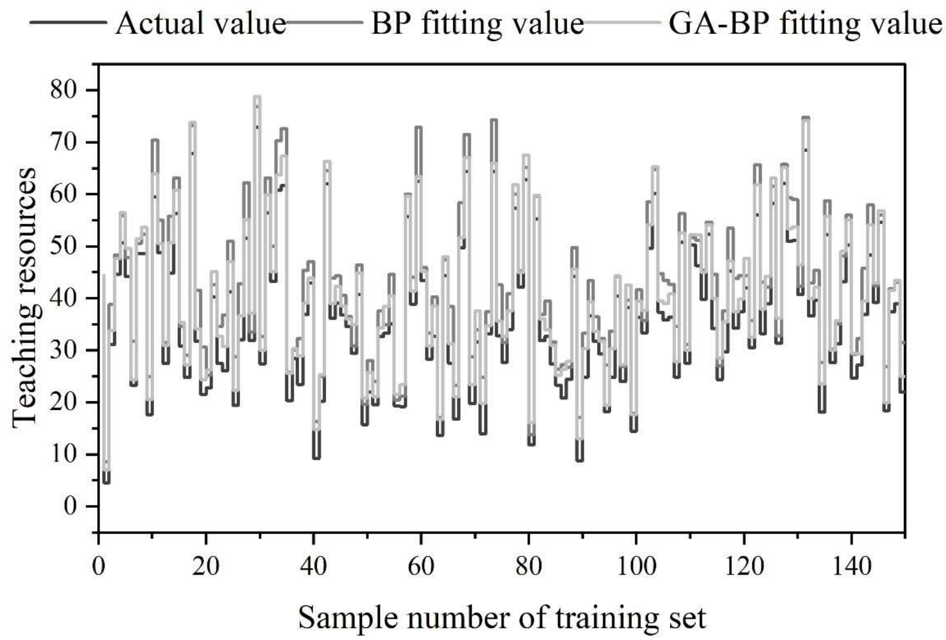


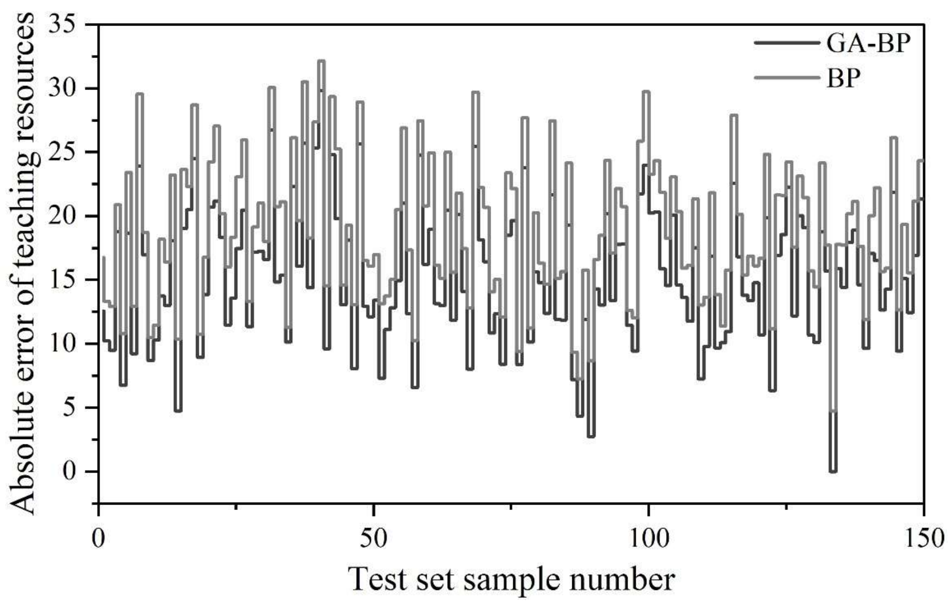
Fig. 3. Optimal individual fitness changes

2) Error comparison. Fig. 4 shows the comparison of test set prediction and error results, Fig. (a) shows the comparison of test set prediction results, and Fig. (b) shows the comparison of test set prediction errors. Based on the GA-BP neural network prediction model and the BP neural network prediction model, the predicted values of the usage of 150 learning resources are obtained respectively and compared with the actual values, and it can be seen from Fig. (a) that both the BPNN and GA-BPNN models can basically realize the prediction of the usage of learning resources.

The magnitude of the change in the error of the prediction value is also one of the factors to assess the performance of the neural network prediction, a good neural network can be more stable simulation prediction, there will not be a large deviation, Figure (a) for the two models to predict the number of citations and the actual number of citations of the absolute error comparison, reflecting the BPNN and the GA-BPNN model of the magnitude of the change in the absolute error. It can be seen that GA-BPNN is obviously better than BPNN, the absolute error of the overall model of GA-BPNN is smaller, almost 90% of the error is smaller than the BPNN model, and the fluctuation amplitude and fluctuation range of the absolute error curve of GA-BPNN is smaller, the mean value of the error of GA-BPNN is around 15.244, while that of the BPNN is 18.901. This indicates that the citation volume of the papers based on the GA-BPNN is lower than that of the actual citation volume of the BPNN model. BPNN-based citation prediction model is more stable and has higher prediction accuracy.



(a)Test set prediction results comparison



(b)Test set prediction error comparison

Fig. 4. Test set prediction compared with error results

3.3. SEM structural equation modeling applications

3.3.1. Basic theoretical knowledge:

1) Constructivist learning theory. Constructivist learning theory emphasizes the active construction of knowledge by students, and online learning is a way to meet the environmental conditions required for the practice of constructivist learning theory, and has become an important theoretical basis for scholars to study the effectiveness of online learning through the constructivist model. Students choose effective online platforms according to their learning needs, improve their knowledge construction through the Internet, and explore the optimal personal learning path.

2) Humanistic learning theory. Maros and Rogers are representative scholars of humanism in the

field of education, and they believe that the focus of teaching activities should be the students rather than teachers. It is because all human beings have the need for self-actualization that human potential can be stimulated.

3.3.2. Analytical framework. Combined with the characteristics of the Internet, a number of latent variables were identified as the influencing factors for predicting the learning effect under the mobile Internet, some mediating factors were set, and based on the research of past scholars, the research model of this study was proposed, and the model diagram is shown in Figure 5.

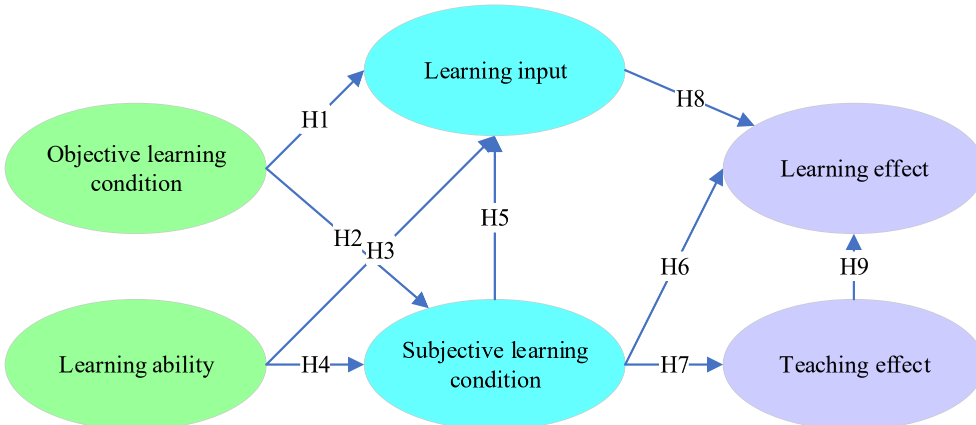


Fig. 5. Default research model

3.3.3. Measurement modeling. The research group established a measurement model of six dimensions of structural equation modeling (SEM) of learning effectiveness, teaching effectiveness, learning input, objective learning conditions, subjective learning factors and learning ability, which represents the relationship between latent and observed variables, integrating factor analysis and path analysis, and the presentation of the model is shown in Equation (15) (16):

$$Y = \Lambda_y \eta + \varepsilon (p \cdot 1)(p \cdot m)(m \cdot 1) \tag{15}$$

$$X = \Lambda_x \xi + \delta (q \cdot 1)(q \cdot a)(q \cdot 1) \tag{16}$$

where Y and X are vectors of endogenous and exogenous observed variables, respectively, and Λ_x and Λ_y denote the matrices of regression coefficients for Y vs. η and X vs. ξ, respectively, i.e., the loading matrices.

3.3.4. Formulation of hypotheses. Table 1 shows the number of hypothesized items against the content of the hypotheses, which were set up based on the pre-determined research model in Figure 5, followed by a hypothetical experiment to test the hypotheses proposed in this paper.

Table 1. Let's say that the number of terms is compared to the hypothesis

Number of assumed terms	Hypothetical content
H1	Objective learning conditions are affecting students' learning input
H2	Subjective learning condition of positive influence of objective learning condition
H3	Learning ability is affecting students' learning input
H4	Subjective learning conditions of the positive impact of learning ability
H5	Subjective learning condition is affecting students' learning input
H6	Subjective learning condition is affecting students' learning effect
H7	Subjective learning condition is affecting the teacher's teaching effect
H8	Learning input is affecting students' learning effect
H9	The teacher's teaching effect is affecting the learning effect of the students

4. Research design and analysis

4.1. Study design

4.1.1. Data sources. Since there is no matching mature questionnaire for the research on the factors influencing the learning effectiveness of French courses under POA and its path optimization, the research team compiled the initial questionnaire after many discussions, taking into account the real situation as well as considering various factors such as learning variability, in the form of a five-point scale, with a total of 73 items for the six latent variables of the questionnaire. The research team first conducted a pilot test of the questionnaire, collected 5,375 pieces of pilot test data for analysis, and according to the results of the analysis, deleted three items that did not meet the standards of reliability and validity and the factor loadings were low, and added the item of the school year to form a formal questionnaire consisting of 71 items, and finally collected 5,375 pieces of questionnaire data.

4.1.2. Reliability analysis of the measurement questionnaire. In this paper, the total scale containing six question items was established, and in order to maintain the internal consistency of the scale, before conducting the exploratory factor analysis, the reliability of the questionnaire answers was first tested by calculating the Cronbach's α (Cronbach's coefficient) value of the internal consistency reliability coefficient of the scale for the internal consistency test by utilizing the sample of 5,375 pieces of data. The research team established measurement models for six dimensions: learning effect, teaching effect, learning commitment, objective learning conditions, subjective learning factors and learning ability to measure their Cronbach's coefficients respectively, and to test the reliability of the scales for the six dimensions.

Table 2 shows the reliability test of the scale. The Cronbach's coefficients of the five latent variables of learning effect, teaching effect, objective learning conditions, subjective learning factors and learning ability are all greater than 0.9, which indicates that they all have good measurement reliability, and the Cronbach's coefficient of learning input (0.8963) is also close to 0.9, which is of considerable measurement reliability. This indicates that the results of this measurement have high consistency, stability and reliability.

Table 2. Reliability test of the scale

Variable	Measure the number of items	Kronbach coefficient
Learning effect(LE)	Q1~15	0.9315
Teaching effect(TE)	Q2~11	0.9126
Learning input(LI)	Q3~9	0.8963
Objective learning condition(OL)	Q4~15	0.9515
Subjective learning factor(SL)	Q5~9	0.9136
Learning ability(LA)	Q6~12	0.9425

4.2. Findings

4.2.1. Basic Analysis of the Sample. Table 3 shows the basic situation of the samples. Among the 5375 samples, there were 975 students in the first year of university, accounting for 19.14%; 1535 students in the second year of university, accounting for 30.13%; 2210 students in the third year of university, accounting for 43.38%; and 375 students in the fourth year of university, accounting for 7.36%. Undergraduates 5,095, accounting for 94.79%, specialists 260, accounting for 4.84%, "college to bachelor" students 20, accounting for 0.37%. The number of volunteers who chose their own specialties was 4080, accounting for 75.91%, the number of parents and others who chose their own specialties was 650, accounting for 12.09%, and the number of students who transferred their specialties was 645, accounting for 12.00%. After graduation, 4136 people want to engage in work related to this specialty, accounting for 76.95%, and 1239 people don't want to engage in work related to this specialty after graduation, accounting for 23.05%. From the viewpoint of employment demand, 1836 people, or 34.16%, thought that their majors were popular majors, 2845 people, or 52.93%, thought that their majors were general majors, and 694 people, or 12.91%, thought that their majors were cold majors.

Table 3. Sample basic information

Name	Options	Frequency	Percent %)
Grade	Freshman Year	975	19.14%
	Sophomore	1535	30.13%
	Junior	2210	43.38%
	Senior Year	375	7.36%
Education Background	Undergraduate	5095	94.79%
	Specialty	260	4.84%
	Special Promotion	20	0.37%
Professional Volunteers Fill In The Information	Autonomous Selection	4080	75.91%
	The Will Of Parents And Others	650	12.09%
	Professional Adjustment	645	12.00%
Whether After Graduation Want To Work In This Field	Yes	4136	76.95%
	No	1239	23.05%
Demand From Employment Look At The Current Edition Business Prospect	Hot Majors	1836	34.16%
	General Major	2845	52.93%
	Cold Door Major	694	12.91%

4.2.2. Sample statistics. The 5375 valid samples were statistically analyzed using SPSS 26.0, and the mean, standard deviation, and other statistical results of each measurement question item are shown in Figure 6. First, the mean value of each measurement item of each variable ranges from 3.424-3.849 points, and in general, the respondents scored high on the six dimensions. Second, the maximum value of each question item of the survey data is 5, and the minimum value is 1. The sample data can be regarded as normally distributed, which satisfies the conditions for subsequent analysis.

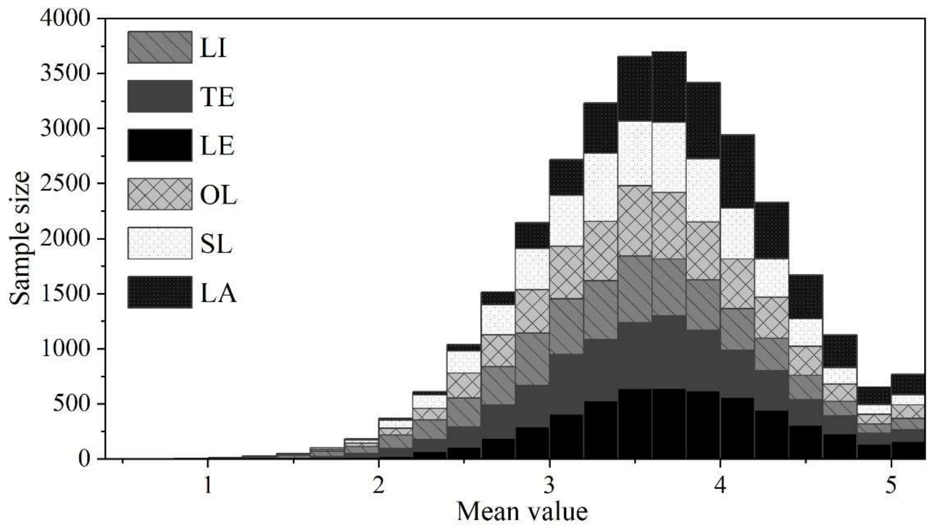


Fig. 6. Sample statistics

4.2.3. Matrix of variable correlations. Figure 7 shows the correlation matrix of the variables involved in the research model, Learning Effectiveness (LE) is positively correlated with Teaching Effectiveness (TE), Learning Input (LI), Objective Learning Condition (OL), Subjective Learning Factors (SL), and Learning Aptitude (LA), with the correlation coefficients of 0.6055, 0.5215, 0.5536, 0.5548, and 0.5436, respectively, and p-values of less than 0.01.

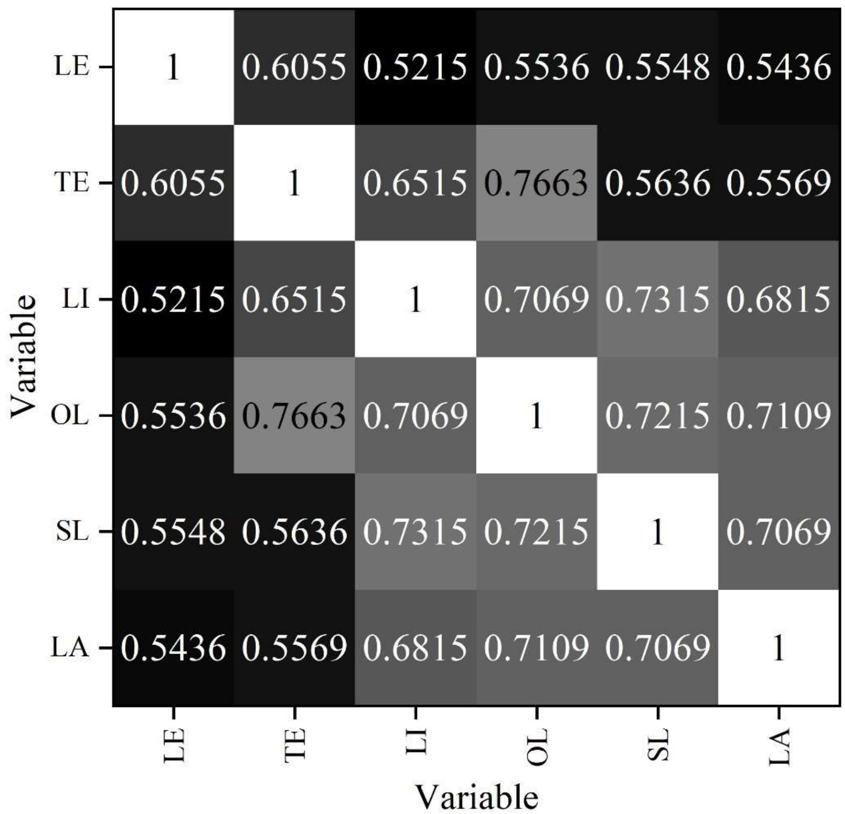


Fig. 7. The correlation matrix of variables involved in the model is studied

4.2.4. Fitting results. Using AMOS23.0 software to analyze the data empirically, the overall fit of the shown model was obtained, as shown in Table 4. The structural equation model of the factors influencing the course learning effectiveness of French majors' college students was constructed with a good fit condition to the data, and the fitted values of the indicators RMSEA, GFI, AGFI, NFI, CFI, RFI, and SRMR were 0.075, 0.916, 0.906, 0.918, 0.913, 0.903, and 0.042, which were in line with the evaluation standards. The causal model of structural equation modeling is supported by the empirical data, indicating that the path analysis hypothesis is valid.

Table 4. The overall fitting evaluation criteria and the proposed results

Index	Calorie value	Freedom	Calorie / Freedom	RMSEA	GFI
Reference standard	The smaller the better	The bigger the better	<3(or 5)	<0.08	>0.9
Fitting value	998.415	225	4.455	0.075	0.916
Fitting evaluation			Ideal	Ideal	Ideal
Index	AGFI	NFI	CFI	RFI	SRMR
Reference standard	>0.9	>0.9	>0.9	>0.9	<0.05
Fitting value	0.906	0.918	0.913	0.903	0.042
Fitting evaluation	Ideal	Ideal	Ideal	Ideal	Ideal

4.2.5. Results of hypothesis testing. Table 5 shows the paths of influence of the constituent dimensions of college students' learning effectiveness in French, which further shows the paths of influence among the observed variables as well as between the latent variables and the observed variables. The path coefficients between the variables and the path coefficients of the factor loadings in the model reached a significant level of 0.000 and were all positive, indicating that the validity of the path coefficients was within an acceptable range. The nine hypotheses H1 to H9 are all supported.

Table 5. College students' French learning effect constitutes a dimension influencing path

Hypothesize			Estimate	S.E.	C.R.	P	Label
Objective learning condition	→	Subjective learning condition	1.126	0.045	27.896	***	Par_2
Learning ability	→	Subjective learning condition	0.916	0.046	19.069	***	Par_4
Objective learning condition	→	Learning input	0.896	0.031	29.645	***	Par_1
Learning ability	→	Learning input	1.035	0.045	23.155	***	Par_3
Subjective learning condition	→	Learning input	0.975	0.043	22.345	***	Par_5
Subjective learning condition	→	Teaching effect	1				Par_7
Teaching effect	→	Learning effect	0.264	0.035	8.466	***	Par_9
Subjective learning condition	→	Learning effect	0.429	0.062	6.951	***	Par_6
Learning input	→	Learning effect	0.226	0.046	5.136	***	Par_8

4.2.6. Recommended Path Learning Survey. Two classes, A and B, majoring in French at a university were selected for controlled experiments. Class A used the output-oriented method to establish learning groups with recommended path learning resources, while class B used the default path recommended instruction for learning.

Table 6 shows the results of comparing the recommended path learning with the default path.The results of the survey of the students in the recommended path learning group (Group A) show that 31.4% of the students know French grammar very well before learning, but there are also 40.32% of the students who are not sure about this issue, and the percentage of disagreement is also as high as 28.27%.

Compared with the default path, 69.78% of the students thought that the recommended learning path was easy to understand, while 20.23% of the students were unsure about it. 56.02% of the students thought that the recommended learning path had a reasonable sequence of courses, while 35.24% of the students were unsure about it. The results of the analysis of the data from the two groups of surveys showed that the learning path constructed on the basis of the output-oriented approach to French language education resources was more effective than the default path. Compared with the default learning path, it can satisfy students' learning needs better.

Table 6. Comparing the recommended path learning with the default path

Investigation problem	Very agree	Consent	Indeterminate	Not agree and quit	Strongly disagree
Recommended path learning results					
Before learning, you know a lot about French grammar	2.81%	28.59 %	40.32%	20.46%	7.81%
After learning, we mastered the concept and application of French grammar	11.44%	28.57 %	40.24%	14.69%	5.06%
It is easy to understand the knowledge of learning path courses	8.32%	48.36 %	31.24%	12.08%	0.00%
The recommended learning path course is set in a reasonable order	17.26%	37.86 %	44.88%	0%	0.00%
Survey result of comparing the recommended path with the default path					
Before learning, you know a lot about French grammar	11.69%	70.36 %	8.81%	5.86%	3.28%
The recommended learning path is easier to understand than the default learning path	17.63%	52.15 %	20.23%	5.83%	4.16%
The recommended learning path is more reasonable than the order of the default learning path	11.79%	44.23 %	35.24%	2.94%	5.80%
The recommended learning path is closer to the actual application than the default learning path sample code	14.74%	50%	26.59%	5.81%	2.50%

4.3. Effectiveness of blended teaching of French based on output orientation

The number of questions completed, the total score, and the scoring rate on different types of questions of the students in Class A were counted as a basis for determining the students' learning effectiveness in French reading.

In terms of the number of completed questions and total scores, Tables 7 and 8 for reading and writing ability respectively, students could complete an average of 30 questions in the pre-test, which rose to 34 in the post-test, and the total scores rose from an average of 4 in the pre-test to 5.5, which shows that the students' speed of doing the questions and the overall accuracy of their reading answers have increased significantly.

For writing skills, syntactic complexity, semantic coherence, and lexical complexity all increased compared to the pre-test, with increases of 12.78, 0.04, and 0.28, respectively.

Table 7. Reading ability

/	Finish the problem	Total score(Full score9)	Accuracy			
			Keynote reading	Detail reading		
			Careless matching	Fill in	Judging	Multiple selection, detail matching
Premeasurement	30	4	34.15%	43.51%	44.51%	38.41%
Posttest	34	5.5	43.26%	24.36%	49.36%	64.25%
Increase	4	1.5	9.11%	-19.15%	4.85%	25.84%
P-value	0.0023	0.0005	0.0001	0.0001	0.0236	0

Table 8. Writing ability

Evaluation dimension	Syntactic complexity	Semantic coherence	Lexical complexity	Lexical complexity Syntactic complexity
Premeasurement	21.82	0.59	0.65	35.61
Posttest	34.60	0.63	0.93	43.48
Increase	12.78	0.04	0.28	7.87
P-value	0.0001	0.0001	0.0236	0

5. Strategies for improving the learning of French among students in higher education

5.1. Student level

5.1.1. Enhancing one's information literacy skills. Improve their information literacy, first of all, explore learning resources more actively through the model constructed in this paper. Actively participate in all kinds of interactive learning content, such as French speaking videos and real-time voice interaction. This not only helps to develop the ability of information acquisition, but also adds interest to learning and makes learning more vivid and interesting. Secondly, pay attention to the connection between learning tasks and real life. Through simulation and role-playing, learning tasks are integrated into real-life scenarios to make learning more practical.

5.1.2. Stimulating intrinsic motivation to learn. Students can increase their motivation to learn French at their own level by Defining clear learning objectives and setting challenging goals. Students can set clear learning goals, such as completing a certain number of speaking exercises per week, as well as challenging goals, such as improving fluency in oral expression. This helps to stimulate the desire for their own progress and increases motivation.

5.2. Teacher level

5.2.1. Increasing students' self-efficacy. In teaching French, especially to students in higher education, teacher support is of crucial importance in enhancing students' self-efficacy. Teachers should actively convey messages of support and encouragement in their teaching. Through timely and positive feedback, teachers can help students recognize their learning efforts and progress, thus enhancing their self-efficacy.

5.2.2. Teacher support to increase students' motivation to learn. Teachers can stimulate students' interest in learning spoken French by designing vivid and interesting teaching contents and combining them with practical cases and stories. In addition, give students positive encouragement and positive feedback in time to help them build up self-confidence and thus enhance their learning motivation. Secondly, teachers should pay attention to students' behavioral input. In order to further enhance students' learning motivation, teachers can adopt task-oriented teaching methods, design tasks related to real life, and guide students to show initiative in learning. By letting students experience the practical use of spoken French, they can stimulate their learning interest and improve their learning motivation. Finally, teachers can also focus on social interaction input. Teachers can organize group activities to encourage students to cooperate and communicate with each other and solve problems together. This not only helps to establish a good learning atmosphere, but also stimulates students' sense of teamwork and improves learning motivation.

6. Conclusion

This paper establishes a French course educational resource based on the output-oriented method, and designs the driving phase, enabling phase and evaluation phase respectively. Meanwhile, GA-BP neural network and SEM structural equation model are associated to reason out the shortest path of French course learning. Through hypothesis testing, the authenticity of the pathway is verified, and the French learning enhancement strategies for college students are proposed at the student and teacher levels.

1) Statistical analysis of the sample, the average value of each variable measurement question item is between 3.424-3.849 points, the investigated subjects have higher scores on the six dimensions, the maximum and minimum values are 5 and 1 points, respectively, the sample data can be regarded as normally distributed to meet the conditions of the subsequent analysis.

2) Constructing the correlation matrix of variables, the correlation coefficients of learning effect with teaching effect, learning input, objective learning conditions, subjective learning factors, and learning ability are 0.6055, 0.5215, 0.5536, 0.5548, and 0.5436, respectively.Further analyzing the influencing paths of learning effect in French, the path coefficients of the various variables in the model as well as the factor loadings of the path coefficients all reach a significant level of 0.000 and all are positive, and the nine hypotheses H1 to H9 are supported.

3) Analyzing the effectiveness of the mixed French teaching model based on output orientation, the total score of reading proficiency increased from 4 to 5.5, while in writing proficiency, syntactic complexity, semantic coherence, and lexical complexity increased compared to the pre-test, with increases of 12.78, 0.04, and 0.28, respectively. It can be seen that the path recommendation in this paper is effective.

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