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The construction and economic empowerment path of "youth night school" education model in higher vocational colleges and universities based on multilayer perceptual machine algorithm

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SUMMARY: *As an open and complementary educational model, the Youth Night School in higher vocational colleges and universities connects students' individualized learning needs and their entrepreneurial economic empowerment. The study categorizes students' learning behaviors in youth night school into four dimensions of testing behaviors, forum interaction, content learning and resource searching, and 11 specific indicators of the observation system. And an improved deep neural network learning resource recommendation algorithm (UDN-CBR) is designed. It deeply mines the relationship between students' learning behaviors and resource attributes by using a multilayer perceptron (MLP), and reads the resource text through a convolutional neural network (CNN). Ultimately, it fuses information from multiple sources to generate personalized learning resource recommendations for students. The study collected valid data and entrepreneurial profitability questionnaires from 354 participating night school students, whose average weekly study hours were above 2h in the middle and late semester, and whose average final test scores (87.67±10.99) were significantly higher than usual (77.95±13.58). Stepwise regression analysis and structural equation modeling validation pointed out that content learning was the most powerful factor in improving profitability with a path coefficient = 0.623, while forum interaction guided business stability with a standardized estimate = 0.588, and resource searching behaviors were the most prominent driver of self-growth performance with a path coefficient of 0.634.*

KEYWORDS: *multilayer perceptron; youth night school; UDN-CBR; entrepreneurial profitability; economic empowerment*

1 Introduction

In recent years, with the rapid economic and social development, students in higher vocational colleges and universities are faced with the double pressure from academic and employment, and their after-school time is often caught in a repetitive and monotonous pattern, which seriously lacks the systematic skills and interests of the cultivation of opportunities [1-3]. In this context, the innovative construction of "youth night school" education model has been emphasized and gradually promoted [4]. "Youth night school" is a more popular form of training for young employees, which has the characteristics of standardized organization, long cycle, obvious effect, etc. Through the systematic, standardized and refined operation mechanism, it has become an effective carrier to serve the rapid growth of young people to become successful [5].

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Although the existing model has a certain degree of effectiveness, in the actual teaching, “youth night school” education model is still facing problems such as poor relevance, uneven matching of teaching resources, etc. In order to effectively transform this situation, the multilayer perceptual machine algorithm (MLP) has been gradually applied, and plays an important role. MLP is a one-way propagation multilayer feed-forward network model, which is one of the most basic network models in neural network research and application due to its high nonlinear mapping ability, and is widely used in the fields of pattern recognition, image processing, function approximation, optimization computation, optimal prediction, and adaptive control, etc. [6-9]. The introduction of MLP in the education model of “Youth Night School” can realize personalized curriculum customization through the analysis of students' learning status, career goals, professional skills, etc., which solves the problem of traditional teaching that cannot meet the personalized needs [10]. In addition, MLP can realize intelligent matching of teaching resources, provide students with real-time learning data by combining with actual cases, and provide learning warning according to the students' learning effect and attitude, so as to adjust the teaching strategy [11, 12]. The education mode of “Youth Night School” under MLP can help to cultivate students' skills more quickly and effectively, and reduce the cost of talent cultivation. The education model of “Youth Night School” under MLP helps to cultivate students' skills more quickly and effectively, reduces the time of talent training and the cost of enterprises in talent training, and indirectly promotes the development of the economy.

The study explores the economic empowerment path of multilayer perceptron in “youth night school” education. Firstly, we cleaned, standardized and standardized the study data of youth night school for higher vocational students. A behavioral indicator system covering four dimensions: testing behavior, forum interaction, content learning and resource search is constructed. Further improve the deep neural network learning resource recommendation algorithm, on the basis of receiving students' learning behavior data, deeply integrate the attributes of learning resources itself and text content. Convolutional neural network (CNN) is utilized to read the textual description of the resources, and then the nonlinear matching relationship between student features and resource features is deeply mined by multilayer perceptron (MLP) to generate a resource recommendation list for students. The resource recommendation-based night school model is eventually put into practice to explore the impact of youth night school learning behavior on entrepreneurial profitability. The students' youth night school learning behavior is directly taken as the independent variable, and the hypothesized relationships between it and the three economic empowerment indicators of profitability, business stability and own growth performance are established. Empirical analysis was conducted by collecting questionnaire data.

2 Study of learning behavior based on UDN-CBR learning resource recommendation

2.1 Data analysis of learning behavior and learning behavior indicator system for youth night schools

2.1.1 Data pre-processing

The data of this paper comes from VLE, an online learning platform for higher vocational students, which stores the data of 2,718 students in the “Youth Night School”. The following three steps of data preprocessing are carried out.

Data cleaning: Some students have garbled codes or formatting errors in fields such as "number of course interactions" and "number of post-course homework submissions", and 186 anomalies are found and corrected. In response to the situation that the "total duration of night school study" was empty, the field was set to 0 for 107 students, indicating that they did not participate in online study. For the records with empty values in "evening school quiz score" and "course completion", the corresponding indexes are uniformly assigned to 0, which is regarded as non-participation in the assessment.

Data Integration: In this paper, one course, Innovation and Entrepreneurship Skills Enhancement, was selected as the target data from the 15 courses in the online learning platform VLE "Youth Night School". The Java program is designed to batch manipulate the original dataset to get the new indicators needed in this paper, and then import the new indicators and the data of the original valid indicators into the MySQL database to store them, set the primary and foreign key relationships of each table, and divide them into two parts during the training process, the first one is the training set, which is used to generate the multilayer perceptual machine model or function, and the second one is the testing set, which is used to evaluate the model.

Data statute and data standardization: since the data mining models selected in this paper have inconsistent standards for data statute, the data statute is processed accordingly when training a specific model. The standardization of data is to make the variables comparable to each other, this paper selects the Z-score formula for standardization from many standardization methods, and the process can be seen in Equation (1)

$$x^{\bullet} = \frac{x-\mu}{\sigma} \tag{1}$$

where σ is the standard deviation of the historical data and μ is the mean of the historical data

2.1.2 Learning behavior indicator system

According to the research needs of this paper on the student platform learning behavior to establish an indicator system, divided into testing behavior indicators, forum interaction behavior indicators, content learning behavior indicators and resource search behavior indicators, specific as shown in Table 1.

Table 1: Learning Behavior Index System

Dimension	Measurement variables
Test behavior	Regular test scores
	Number of completed regular tests
	Final test scores
Forum interaction behavior	Duration of forum visits
	Number of forum discussions participated in
Content learning behavior	Number of visits to course content
	Duration of video viewing
	Duration of text resource viewing
Resource search behavior	Times learning resources were downloaded
	Tmes the platform encyclopedia was queried
	Times the reference vocabulary list was consulted

2.2 MLP Improved Deep Neural Network Learning Resource Recommendation Algorithm

For the recommendation of learning resources in the process of online learning, the paper proposes a learning resource recommendation algorithm that improves the DN-CBR model, and the improved model is called UDN-CBR model. At the same time, the above students' youth night school learning behavior data are inputted into the model, so that the model can give corresponding resource recommendations based on different students' behavior data.

The algorithm follows the advantages of the DN-CBR model, combines the learners' learning behavior data and learning resources information, and uses the powerful feature extraction ability of deep neural networks to fully learn the nonlinear relationship between learners and learning resources. The model framework is shown in Figure 1 below.The UDN-CBR model is divided into four phases, which are acquiring attribute features of learners and learning resources, convolutional neural network acquiring textual features of learning resources, combining attribute features and textual features of learning resources and MLP predicting scores and generating recommendations.

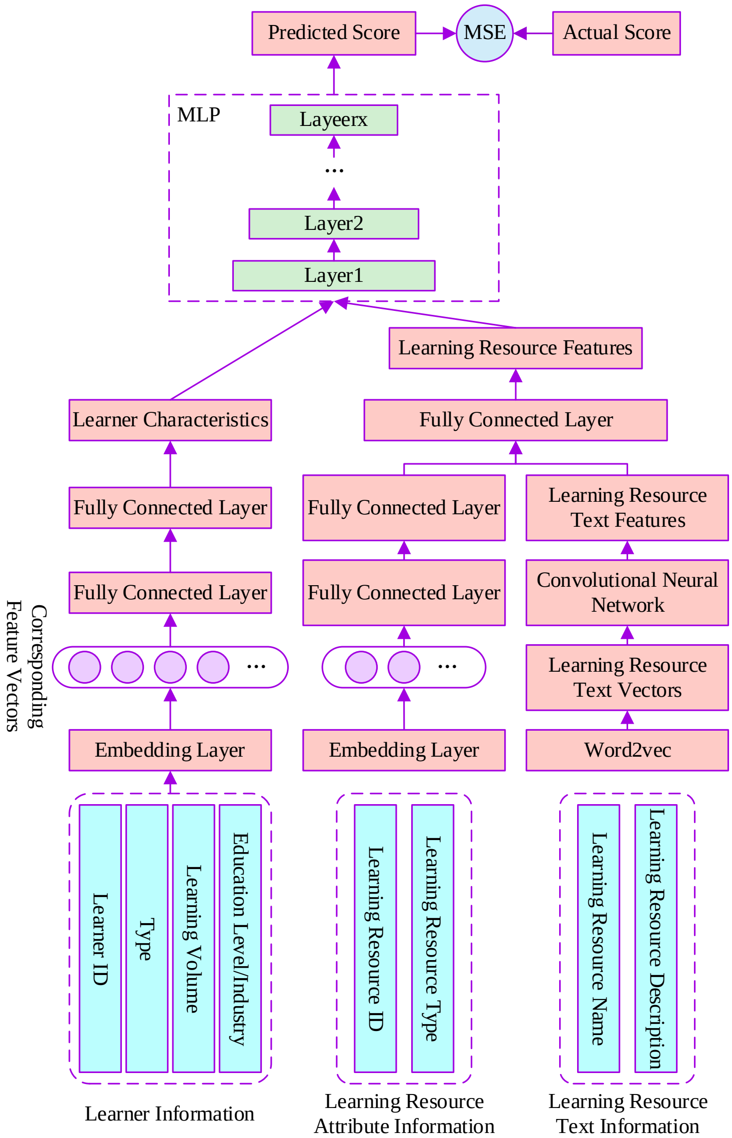

Figure 1: UDN-CBR Model Framework

2.2.1 Access to attribute characteristics of learners and learning resources

The learner youth night school learning behavior information and learning resource attribute information based on Section 2.1 are inputted into the UDN-CBR model to obtain the attribute characteristics of the learner and learning resources. Suppose the attributes of learners are $x:\{x_1, x_2.....x_m\}$, and x_i denotes one of the learner attributes, e.g., the length of time the learner visits the forum. The attributes of a learning resource can be represented as $y:\{y_1, y_2.....y_n\}$, y_j denotes one of the learning resource attributes, such as learning resource ID. The attributes of the learner and the learning resource are then inputted into the embedding layer to obtain the feature vectors of the learner and the learning resource attributes $\overline{x}$, $\overline{y}$.

$$\overline{x} = f\left(w_1 x + b_1\right) \tag{2}$$

$$\overline{y} = f\left(w_2 y + b_2\right) \tag{3}$$

where w_1 and w_2 denote weights, b_1 and b_2 denote biases, and $f\left(\cdot\right)$ denotes activation function.

Then the $concatenate\left(\cdot\right)$ function is used to fuse each attribute feature of the learner to get the learner feature u_i:

$$u_i = concatenate\left(\overline{x}\right) \tag{4}$$

Similarly the attribute feature s_j of the learning resource is obtained:

$$s_j = concatenate\left(\overline{y}\right) \tag{5}$$

2.2.2 Convolutional Neural Networks to Acquire Textual Features of Learning Resources

The convolutional neural network in the UDN-CBR model is mainly used to obtain textual features of learning resources from the textual information of learning resources. The text information of learning resources is firstly expressed into the form of text vector of learning resources through Word2vec, and then input into the convolutional neural network to extract the features. The structure of the convolutional neural network model contains four layers, which are embedding layer, convolutional layer, pooling layer and fully connected layer, and the schematic diagram is shown in Figure 2.

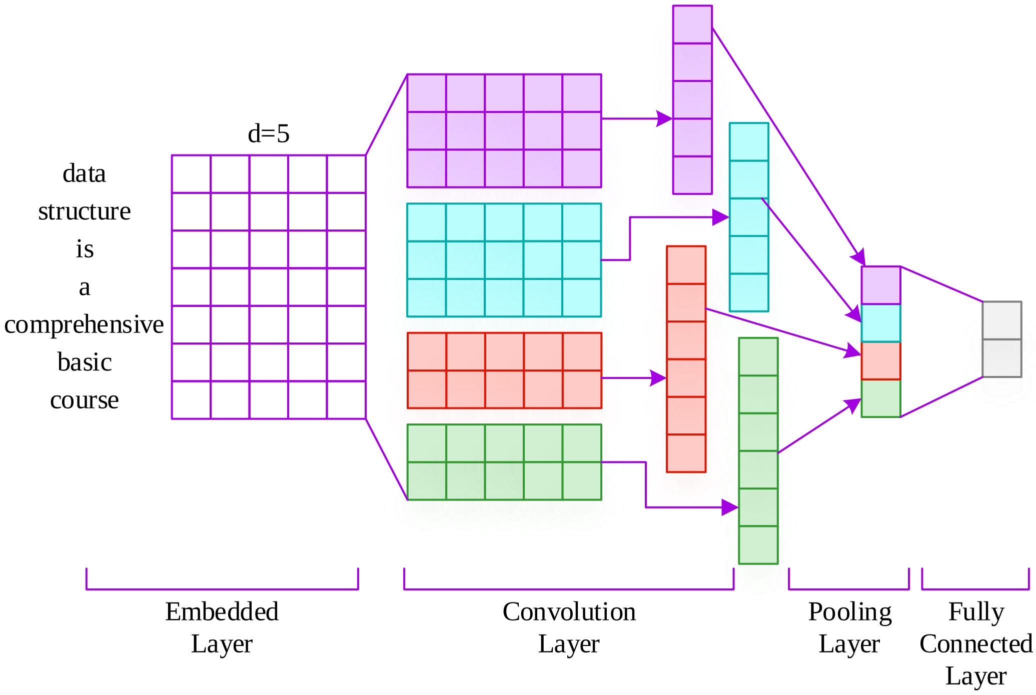

Figure 2: Convolutional Neural Network model

(1) Embedding Layer

The embedding layer is used to convert the textual information of learning resources into an embedding matrix, and each row in the matrix is a participle element. As shown in Figure 2 embedding layer, assuming that we have a total of seven words, each word is represented by a 5-dimensional vector, then we can get a 75-dimensional matrix, this matrix is equivalent to an "image" for the convolution layer for convolution operations. The text matrix of the learning resource $D \in R^{n*m}$ can be expressed as follows:

$$\begin{bmatrix} w_{11} & \cdots & w_{1i} & \cdots & w_{1m} \\ w_{21} & \cdots & w_{2i} & \cdots & w_{2m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{ni} & \cdots & w_{nm} \end{bmatrix} \tag{6}$$

where m represents the dimension of the embedding, n represents the number of words, and $w_{[i,1:m]}$ represents the vector form of the ith word.

(2) Convolutional Layer

The convolution layer uses multiple convolution kernels of different sizes (window size) to do convolution on the embedding matrix, the window size refers to how many words are covered by each convolution. The difference between the image to do the convolution, image convolution kernel is usually used 33, 55 and other sizes, there is no limit to the size of the size, while the text convolution to cover the entire word embedding vector, so the size of the size of the format: the number of words vector dimensions. As shown in Figure 2 in the convolution layer, the use of four different sizes of convolution kernel (2 35, 2 25) were 75 embedding matrix convolution operation, the size of the size of the 35 convolution kernel sliding 3 words each time, the size of 25 convolution kernel sliding 2 words each time, and ultimately the formation of four different feature maps. This shows that there is a one-to-one correspondence between the feature map and the convolution kernel. The formula for the feature map is as follows:

$$m_i = f\left(D * F_i + b_i\right) \tag{7}$$

where * denotes the convolution calculation, b_i denotes the bias term, and $f(\cdot)$ is a nonlinear activation function, which can be used to introduce nonlinear factors into the model, and to solve the feature vectors that are difficult to be represented by linear models, and the ReLU function is used in this model.

(3) Pooling layer

The pooling layer is mainly used after the convolutional layer to reduce the dimension of the feature map and the number of network parameters through the downsampling operation. The commonly used pooling operations include mean pooling and maximum pooling. The pooling operation can ignore the small changes in the feature map to improve the accuracy, and at the same time, it can effectively avoid the phenomenon of overfitting. Assuming that the feature map obtained in the ith convolutional layer is $M_t = \{m_1, m_2, \cdots, m_s\}$, the maximum pooling is used to extract the maximal value in M_t, and p_t denotes the pooling result of the tth convolutional layer, which is formally expressed as:

$$p_t = \max\left(M_t\right) = \max\left\{m_1, m_2, \cdots, m_s\right\} \tag{8}$$

(4) Fully Connected Layer

Usually the network will set up a fully connected layer after the pooling layer, and the main role of the fully connected layer is to synthesize the feature values extracted earlier and output a fixed-size feature vector. Assuming that there are m neurons in the fully connected layer, after the ReLU activation function, a fixed size vector s is obtained, which is the text feature vector of the learning resource. The calculation formula is as follows:

$$s = \mathrm{Re}LU\left(w_i p_i + b_i\right) \tag{9}$$

where p_i denotes the output of the learning resource text information on the pooling layer, w_i denotes the weight, and b_i denotes the corresponding bias. With the above description, the CNN model constitutes a function where the input data is the text information of the learning resources and the output result is the feature vector of each text information.

$$t_j = cnn\left(W, Y_j\right) \tag{10}$$

where W denotes all the weights and bias variables, Y_j denotes the original textual information of learning resource j, and t_j denotes the textual feature vector of learning resource j.

2.2.3 Combining attribute features and textual features of learning resources

The attribute feature of learning resource j is s_j from Eq. (5), and the text feature of learning resource j is t_j from Eq. (10), so the feature v_j of learning resource j can be expressed as:

$$v_j = s_j + t_j \tag{11}$$

2.2.4 MLP predicts scores and generates recommendations

The learner features u_i obtained from Eq. (4) and the learning resource features v_j obtained from Eq. (11) are fed into the multilayer perceptron to predict the scores. The input vector x_0 of the input layer of the multilayer perceptron is to fuse the features of the learner and the learning resources, which is calculated in Equation (12).

$$x_0 = concatenate\left(u_i, v_j\right) \tag{12}$$

In this case, the $concatenate(\cdot)$ function is used to concatenate the features of the learner and the learning resource, and the output value of x_0 after the first layer is represented as:

$$x_1 = f\left(W_1 x_0 + b_1^i\right) \tag{13}$$

where W_1 denotes the weight matrix between the output layer and the first hidden layer, b_1^i denotes the bias vector, and $f(\cdot)$ denotes the activation function. The final output layer formula is shown in equation (14).

$$x_l = f\left(W_l x_{l-1} + b_l^i\right) \tag{14}$$

The predictive score of the model is the:

$$\hat{y} = x_l \tag{15}$$

Finally, a recommendation list is generated for the learner based on the predictive scores provided by the UDN-CBR model.

3 Empirical Analysis of Learning Behavior Characteristics and the Effectiveness of Recommendation Algorithms

Based on the recovered samples, a comprehensive descriptive analysis of the learning behaviors of youth night school students in section 2.1.2, such as study duration, test performance, resource search and interaction behavior, is conducted to reveal the overall characteristics of students' learning behaviors. Immediately after that, the constructed UDN-CBR personalized recommendation algorithm is run to verify whether the algorithm can achieve accurate push according to the person by comparing the stereoscopic differences in the recommendation of learning resources before and after the intervention of the algorithm.

3.1 Analysis of Learning Behavior in Youth Night Schools

A survey was distributed to 388 students who participated in the “Youth Night School” education in a higher vocational college, and 362 copies were finally recovered, with 354 valid questionnaires, a recovery rate of 93.30%, and a validity rate of 97.79%. Firstly, the data on the learning behavior of these 354 students in the youth night school were analyzed.

3.1.1 Analysis of learning hours

Firstly, based on the forum interaction behavior and content learning behavior, the total learning hours, accessing forum hours, video learning hours and text learning hours of the students for a total of 21 weeks in a semester from February 26, 2024 to June 14, 2024 were analyzed with the course "Innovative and Entrepreneurial Skills Enhancement" as the research object.The average weekly learning hours of 354 students are shown in Figure 3.

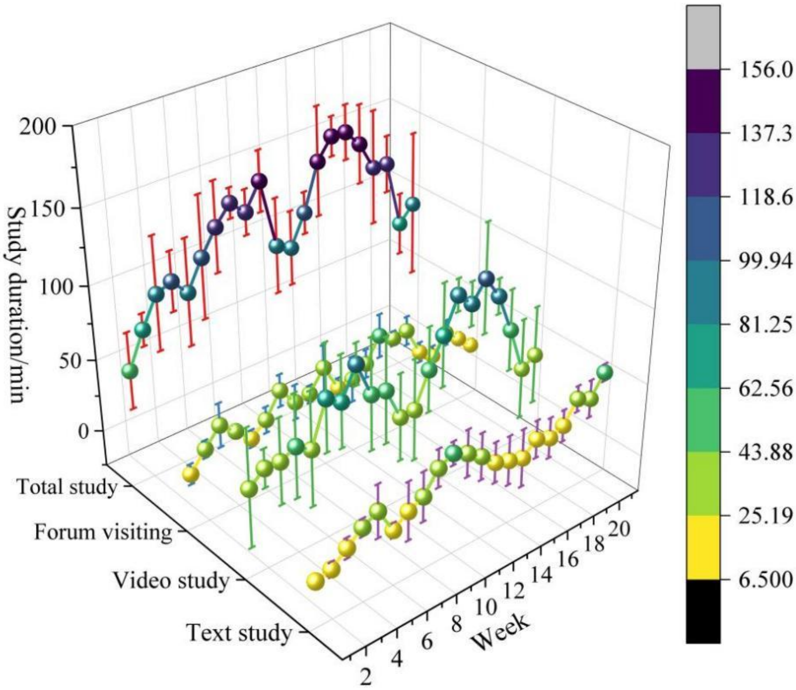

Figure 3: The average weekly study time of 354 students

Students' learning of the Youth Night School's "Innovation and Entrepreneurship Skills Enhancement" course shows a learning process that starts from shallow to deep and gradually focuses on the subject. At the beginning of the semester, the average weekly study time of students was about 54 minutes, most of which was spent on watching videos. As the course progressed, the learning commitment continued to increase and peaked in weeks 15 and 16, with an average weekly learning time of over 155 minutes. During this period, video learning accounted for the highest percentage of study time, especially in weeks 15-18 near the end of the semester, when students averaged 75.17-100.45 minutes of video learning per week. In contrast, the length of time spent on text learning and forum access, while increasing volatility during the midterm and final weeks, accounted for a relatively small percentage overall. At the same time, it can be found that the standard deviation of learning time is large, indicating that different students have large differences in their learning time investment behaviors, and the subsequent recommendation of resources should be based on the students' learning time to achieve personalized differentiated recommendation.

3.1.2 Analysis of test behavior data

Then based on the testing behavior, the students' usual test scores and final test scores were analyzed, and the distribution of both is shown in Figure 4.

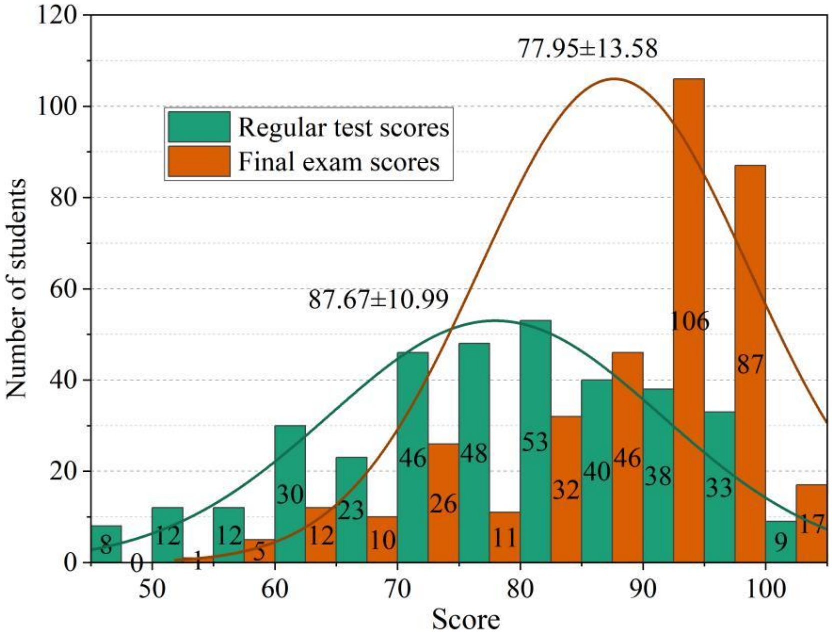

Figure 4: Distribution of students' test scores of regular and final test scores

During the students' learning process in the Youth Evening School of the “Innovation and Entrepreneurship Skills Enhancement” course, the average score of the usual test was 77.95±13.58, and the distribution of the scores was relatively decentralized, covering from failing to perfect scores, and the students' mastery in their daily learning varied greatly. However, most of them performed well in the final test, with an average score of 87.67±10.99, 210 of them gathered in the high score range above 90, and even 17 of them achieved a perfect score, and the distribution of the scores showed right skewness. There are two speculations about this, one is that after a semester of online learning in the youth night school, the final review produces significant effects, and the student group effectively masters the knowledge of the course; the other is that the students don't pay much attention to the usual test, and the usual scores are low under burnout.

3.1.3 Analysis of resource search behavior data

Then, based on the resource searching behavior and other data, the performance of students in terms of the number of times they completed the usual tests, the number of times they participated in the forum discussions, the number of times they accessed the course content, the number of times they downloaded the learning resources, the number of times they queried the platform's encyclopedia, and the number of times they referred to the glossary was obtained as shown in Figure 5.

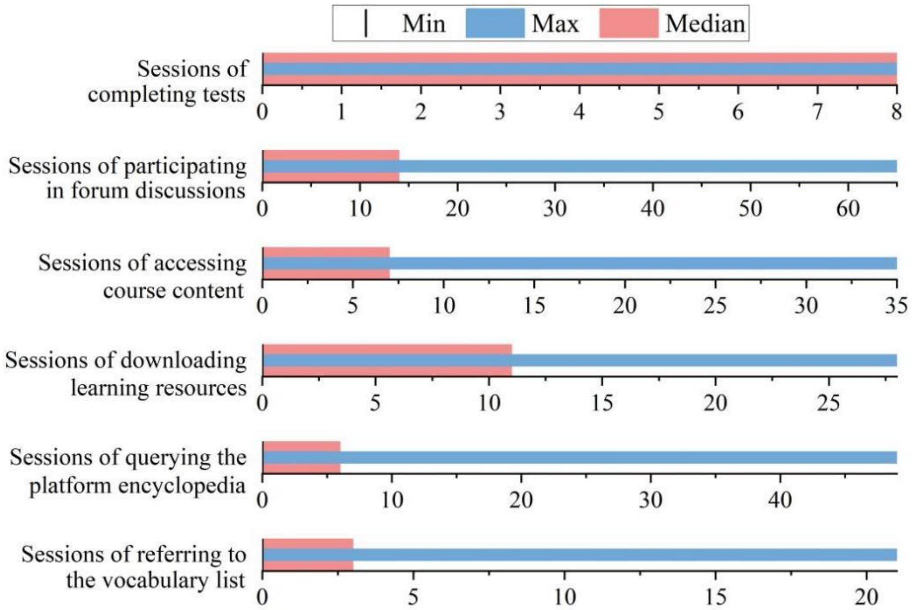

Figure 5: Analysis of Resource Search Behavior Data

The “number of times students completed regular tests” and “number of times students downloaded learning resources” were the most outstanding, with median values of 8 and 11 respectively, indicating that most students were able to complete basic learning tasks and actively download materials for extended learning. However, the behaviors of forum discussion and knowledge query show greater individual differences. For example, the maximum number of times participating in forum discussions was as high as 65, but the median was only 14, implying that a small number of students were highly active in the forums, while the majority of students were moderately or minimally engaged. Similarly, the difference between the maximum value and the median value of the number of platform encyclopedia inquiries and the number of references to the glossary is obvious (49→6 and 21→3, respectively), and the minimum value of these six data indicators is 0. In the evening study of the course of Enhancing Innovative and Entrepreneurial Skills, the students' exploratory and interactive behaviors are not homogeneously distributed, but show a long-tail characteristic centered on the completion of the basic tasks, supplemented by the in-depth participation of some students.

3.2 Analysis of the effect of learning resources recommendation

In order to verify that the deep neural network learning resource recommendation algorithm based on MLP improvement proposed in this paper gives different learning resource recommendation effectiveness based on different performances of students after inputting students' night school learning behavior data, the distribution state of resource recommendation before and after the application of the algorithm is analyzed.

Randomly selected 5 students, and 10 knowledge points, each knowledge point contains 5 learning resources, Figure 6 and Figure 7 are the three-dimensional comparison of learning resources recommended before and after the application of the UDN-CPR algorithm, respectively. X indicates the knowledge point, Y indicates the learning resources contained under it, different colors indicate different learners, and 0 = not recommended, 1 = recommended in the Z output sequence.

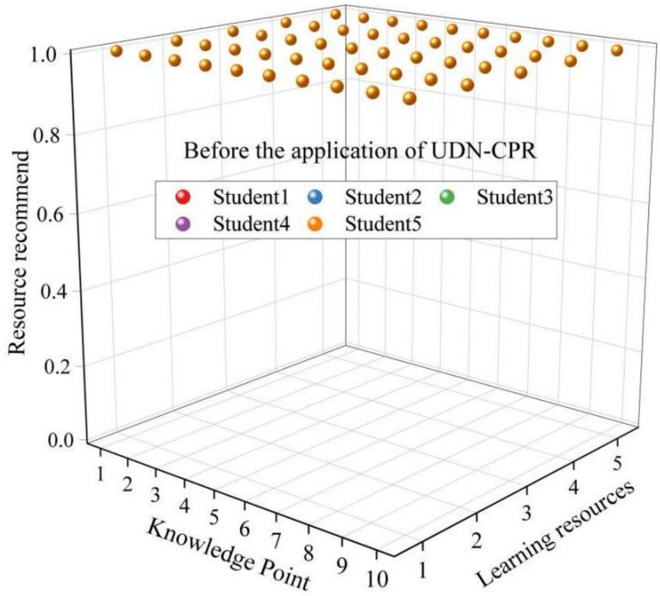

Figure 6: Learning resource recommendation before applying the UDN-CPR

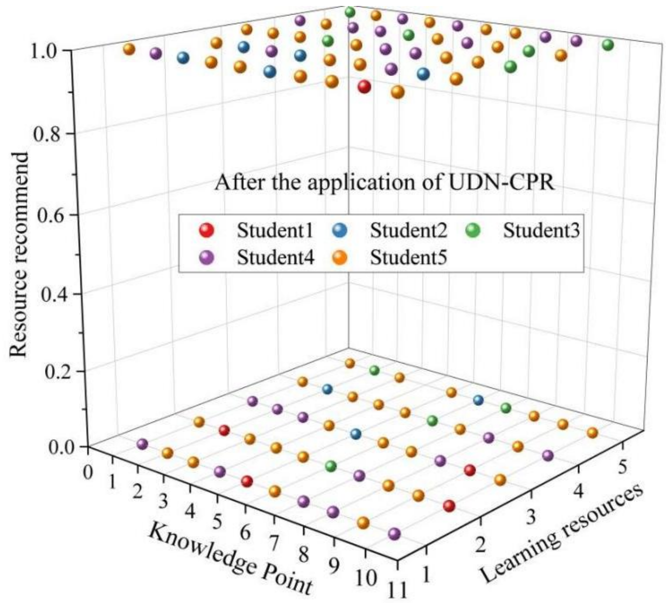

Figure 7: Learning resource recommendation after applying the UDN-CPR

Before applying the UDN-CPR algorithm, Figure 6 learning resources are uniformly distributed at Z=1, i.e., the system recommends all 50 learning resources for 10 students and 10 knowledge points, and there is no differentiated recommendation among different learners with individual differences, and the resource recommendation effect is general. After applying the UDN-CPR algorithm based on students' learning behavior data and resource attributes, different resources for different knowledge points are different from one person to another, realizing significantly differentiated recommendations. Taking Student 1 as an example, for Knowledge Point 1 and Knowledge Point 2, the (1,1,1) and (2,3,1) coordinate points illustrate that it is recommended only in the first and third resources. Fig. 7 The differential distribution of data points indicates that the UDN-CBR model personalizes recommendations for students with respect to the different learning preferences reflected in the input student learning behavior data. Instead of recommending all, the system accurately labels the learning resources that are most needed for a particular individual, improving learning efficiency and resource utilization.

4 Validation of the mechanism of learning behavior on entrepreneurial profitability

After obtaining the characteristics of students' learning behaviors and verifying the efficacy of the personalized recommendation model based on multi-layer perception algorithm, corresponding hypotheses are proposed and verified. Multiple linear regression analyses are conducted to quantify the independent contributions of four types of behaviors, namely, testing, interaction, content learning, and resource search, to the three economic empowerment dimensions, namely, profitability, business stability, and self-growth performance, so as to preliminarily reveal the key driving factors. A structural equation model on entrepreneurial profitability is then constructed and validated to test the significance of all hypothesized paths.

4.1 Impact of Youth Night School Learning on Entrepreneurial Profitability

4.1.1 Research hypothesis

The study explores the education mode and economic empowerment path of “youth night school” in higher vocational colleges and universities, taking the impact of youth night school learning on entrepreneurial profitability as the entry point, with students' learning behavior as the independent variable and entrepreneurial profitability as the dependent variable, and exploring economic empowerment from the three aspects of profitability, business stability and their own growth performance.

In this regard there is hypothesis H1: Youth night school testing behavior has a significant positive impact on entrepreneurial profitability;

H1a: Youth night school testing behavior has a significant positive effect on profitability;

H1b: youth night school testing behavior has a significant positive effect on business stability;

H1c: youth night school testing behavior has a significant positive effect on own growth performance;

Hypothesis H2: Youth night school forum interaction behavior has a significant positive effect on entrepreneurial profitability;

H2a: youth night school forum interaction behavior has a significant positive effect on profitability;

H2b: youth night school forum interaction behavior has a significant positive effect on business stability;

H2c: youth night school forum interaction behavior has a significant positive effect on own growth performance;

Hypothesis H3: youth night school content learning behavior has a significant positive effect on entrepreneurial profitability;

H3a: youth night school content learning behavior has a significant positive effect on profitability;

H3b: Youth night school content learning behavior has a significant positive effect on business stability;

H3c: youth night school content learning behavior has a significant positive effect on own growth performance;

Hypothesis H4: youth night school resource search behavior has a significant positive effect on entrepreneurial profitability;

H4a: youth night school resource search behavior has a significant positive effect on profitability;

H4b: Youth night school resource search behavior has a significant positive effect on business stability;

H4c: youth night school resource search behavior has a significant positive effect on own growth performance.

4.1.2 Study design and measurement of variables

In order to test the aforementioned hypotheses, a survey was conducted to analyze the students who participated in the education model of "Youth Night School" in a higher vocational college, and a questionnaire related to economic empowerment and entrepreneurial profitability was distributed to them, which contained 9 items. The scale was measured using a Likert scale, with "1" representing total disagreement and "5" representing total agreement, increasing from 1 to 5. The entrepreneurial profitability scale and its reliability analysis are shown in Table 2.

Table 2: Business Startup Profitability Scale and Its Reliability Analysis

<table>
<tr><th>Dimension</th><th>Question Item</th><th>Cronbach's α</th></tr>
<tr><td rowspan="3">Profitability</td><td>Through evening school studies, I can more effectively enhance the profit margin of my entrepreneurial project.</td><td rowspan="3">0.876</td></tr>
<tr><td>The evening school courses helped me master the methods of controlling costs, thereby improving the profit level.</td></tr>
<tr><td>The marketing and sales skills I learned in the evening school directly promoted the growth of revenue.</td></tr>
<tr><td rowspan="3">Business stability</td><td>The evening school education enhanced my ability to maintain customers, resulting in an increase in customer repeat purchase rate.</td><td rowspan="3">0.854</td></tr>
<tr><td>After learning the evening school courses, the monthly income fluctuations of my entrepreneurial project significantly decreased and became more stable.</td></tr>
<tr><td>The evening school training helped me focus more on the main business, reducing the risks brought about by business dispersion.</td></tr>
<tr><td rowspan="3">Self-growth performance</td><td>Through evening school studies, I made significant progress in entrepreneurial skills.</td><td rowspan="3">0.901</td></tr>
<tr><td>I can effectively apply the knowledge I learned in the evening school to actual entrepreneurial scenarios and achieve visible results.</td></tr>
<tr><td>After participating in the evening school learning, my confidence in achieving continuous profitability and career growth in the future has significantly increased.</td></tr>
</table>

The Cronbach's alpha coefficients of the three dimensions of profitability, business stability and own growth performance in the entrepreneurial profitability scale are 0.876, 0.854 and 0.901, respectively, which are all above 0.8, indicating that the scale has a good credibility and can be analyzed subsequently.

4.2 Regression analysis of youth night school learning behavior on entrepreneurial profitability

In order to further study the impact of the four dimensions of youth night school learning test behavior, forum interaction, content learning and resource search on entrepreneurial profitability in higher vocational colleges and universities, and to examine in depth the extent of the impact of their different levels on economic empowerment, this study establishes a multiple linear regression model to describe the relationship between the research variables. Taking the 3 dimensions of entrepreneurial profitability (profitability, business stability and self-growth performance) as the validity scale respectively, and adopting the stepwise regression method, the 4 dimensions of the youth night school learning behavior are entered into the regression equation as the independent variables, and the regression analysis of the youth night school learning behavior on entrepreneurial profitability is shown in Table 3.

Table 3: Regression Analysis of Learning Behaviors on Entrepreneurial Profits (N=354)

		Beta	F	p	R^2
Profitability	Total	0.301	19.192	0.000	0.392
	Testing behavior	0.274	18.325	0.003	
	Forum interaction behavior	0.158	7.142	0.062	
	Content learning behavior	0.403	25.618	0.000	
	Resource search behavior	0.102	3.891	0.214	
Business stability	Total	0.278	18.793	0.001	0.337
	Testing behavior	0.226	12.753	0.011	
	Forum interaction behavior	0.318	20.441	0.000	
	Content learning behavior	0.195	9.876	0.024	
	Resource search behavior	0.084	2.345	0.327	
Self-growth performance	Total	0.282	18.906	0.001	0.421
	Testing behavior	0.321	20.911	0.000	
	Forum interaction behavior	0.265	15.782	0.002	
	Content learning behavior	0.307	19.328	0.000	
	Resource search behavior	0.386	28.134	0.000	

In terms of profitability, content learning has the greatest influence, Beta=0.403, F=25.618, p=0.000, while testing behavior also contributes significantly, Beta=0.274. while the direct contribution of learning behaviors in both forum interaction and resource search to short-term profitability is statistically insignificant, with p-values of 0.062 and 0.214, respectively.

When the goal shifts to business stability, forum interaction behavior becomes the most significant influence in the equation, Beta=0.318, p=0.000. testing behavior and content learning also contribute significant positive effects, while resource search still shows no direct effect here, Beat=0.084, p=0.327.

At the self-growth performance level, all behavioral data reached significant impact. The standardized regression coefficient of resource search behavior Beta=0.386, p=0.000 is the first driver of personal competence growth. Testing behavior, forum interaction behavior, and content learning behavior were equally significant at Beta=0.321, 0.265, and 0.307.

4.3 Factor Analysis of Structural Equation Modeling of Entrepreneurial Profitability

Based on the hypotheses presented in section 4.1.1, a validation factor analysis was conducted to analyze the structural equation model of entrepreneurial profitability of students from higher education institutions participating in the youth night school. The structural equation model parameter estimates are shown in Table 4. (e denotes the measurement error of the variable) where based on the above regression analysis it is known that testing behavior → own growth performance, forum interaction behavior → business stability, content learning behavior → profitability and resource search behavior → own growth performance have a significant impact, so the path assignment = 1 is not estimated.

Table 4: Parameter estimation of the entrepreneurial profit structure equation model

	Unstandardized estimate	Standardized estimate	S.E	C.R	P
Testing behavior → Business profit	0.327	0.416	0.078	4.192	0.000
Forum interaction behavior → Business profit	0.285	0.392	0.069	4.131	0.000
Content learning behavior → Business profit	0.412	0.507	0.081	5.086	0.000
Resource search behavior → Business profit	0.238	0.361	0.065	3.662	0.000
Testing behavior → Profitability	0.274	0.348	0.071	3.859	0.000
Testing behavior → Business stability	0.226	0.312	0.068	3.324	0.001
Testing behavior → Personal growth performance	1.000	0.459	—	—	—
Forum interaction behavior → Profitability	0.208	0.294	0.085	2.859	0.003
Forum interaction behavior → Business stability	1.000	0.588	—	—	—
Forum interaction behavior → Personal growth performance	0.265	0.386	0.073	3.632	0.000
Content learning behavior → Profitability	1.000	0.623	—	—	—
Content learning behavior → Business stability	0.195	0.287	0.077	2.532	0.011
Content learning behavior → Personal growth performance	0.222	0.308	0.081	3.206	0.000
Resource search behavior → Profitability	0.202	0.255	0.088	2.159	0.007
Resource search behavior → Business stability	0.184	0.208	0.090	1.833	0.051
Resource search behavior → Personal growth performance	1.000	0.634	—	—	—
e1 Testing behavior	0.703	0.551	0.102	10.892	0.000
e1 Forum interaction behavior	0.682	0.518	0.098	8.959	0.000
e3 Content learning behavior	0.614	0.492	0.089	7.899	0.000
e4 Resource search behavior	0.745	0.573	0.105	11.095	0.000
e5 Business profit	0.588	0.447	0.091	6.462	0.000
e6 Profitability	0.621	0.503	0.095	7.537	0.000
e7 Business stability	0.654	0.527	0.097	7.742	0.000
e8 Personal growth performance	0.592	0.466	0.088	6.727	0.000
e9 Regular test scores	0.433	0.358	0.076	5.697	0.000
e10 Number of regular test completions	0.512	0.414	0.082	6.244	0.000
e11 Final test scores	0.387	0.324	0.071	5.451	0.000
e12 Duration of forum visits	0.498	0.401	0.079	6.304	0.000
e13 Number of forum discussions participated	0.523	0.426	0.083	6.301	0.000
e14 Number of course content visits	0.476	0.388	0.077	6.182	0.000
e15 Video viewing duration	0.441	0.367	0.074	5.959	0.000
e16 Text resource viewing duration	0.465	0.379	0.078	5.962	0.000
e17 Number of learning resource downloads	0.507	0.412	0.081	6.259	0.000
e18 Platform encyclopedia query times	0.489	0.397	0.080	6.113	0.000
e19 Reference vocabulary table times	0.472	0.385	0.078	6.051	0.000

Hypotheses on H1 test behavior series are confirmed. Test behavior is significantly driven on entrepreneurial profitability as a whole, standardized estimate = 0.416, $p<0.001$, and its coefficients on profitability and business stability paths are 0.348 and 0.312, respectively, verifying hypotheses H1a and H1b. Its effect on own growth performance is fixed as a critical path, with a standardized effect value = 0.459, verifying hypothesis H1c.

The H2 series of forum interaction behaviors is also all significant, and it is most significant on the path of improving business stability, with a standardized path coefficient of 0.588, verifying H2b; it also shows positive effects on profitability and own growth performance, $\beta=0.294/0.386$, $p=0.003/0.000$), and H2a and H2c are established.

With respect to content learning behavior, as described in the regression analysis above, it is the strongest determinant driving profitability, with a standardized path coefficient as high as 0.623, validating hypothesis H3a. It also has a slightly weaker, but significant, contribution to business stability, $\beta=0.287$, $p=0.011$, with H3b holding. It has an equally significant effect on its own growth performance, $\beta=0.308$, $p=0.000$, H3c holds.

There is a unique non-significant path in terms of Resource Search Behavior, which has a standardized coefficient of 0.184 on Business Stability, with a critical value of $C.R=1.833<1.9$, $p=0.051>0.05$, and the hypothesis H4b is not supported and therefore does not hold. However, its overall contribution to entrepreneurial profitability as a whole remains significant with $\beta=0.361$, $p=0.000$, and its path coefficient on profitability and its own growth performance is 0.255 and 0.634, which are significant up to the level of 0.01 and 0.001, respectively, and hypotheses H4a and H4c are valid.

5 Conclusion

The study explores how youth night school in higher vocational colleges and universities can empower students' entrepreneurial path, and the findings can be summarized as follows: learning behavior can be measured, personalized recommendation can be realized, and economic empowerment can be verified.

Through the analysis of the behavioral data of 354 students in one semester, it was found that the average weekly study hours of students gradually climbed from 54min at the beginning to more than 155min after the midterm, forming an input deepening curve. This input translates into tangible results, as the average score of the student group on the final test was 87.67, a significant and concentrated improvement compared to the usual score of 77.95, proving that youth night school learning is effective.

The improved UDN-CBR algorithm based on MLP is similarly demonstrated, and the 3D comparison graph visually shows that the algorithm's intervention transforms the 50 resources that were uniformly recommended to all people into personalized recommendations that vary from person to person.

Revealing the paths of different learning behaviors transforming to economic empowerment, the content learning behavior → profitability is the strongest, path coefficient = 0.623; the forum interaction behavior → business stability path coefficient = 0.588; the resource searching behavior → self-growth performance path coefficient = 0.634. All the paths have critical value C.Rs of almost 1.9 or above, and based on the assumption of H4b, the resource searching behavior → business Stability path is excepted, its standardized path coefficient = 0.208, C.R = 1.833, which is not significant, hypothesis H4b is not valid, and the path is deleted.

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