J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 8845--8859

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on predicting the adaptability of employment policy for senior college students based on collaborative filtering algorithm

Yangzi Chen[1,✉], Sheng Qin[2]

[1] *Department of Air Transport, Shanghai Civil Aviation College, Shanghai, 200120, China*
[2] *Department of Aircraft Flight Test, China Commercial Flying Company Civil Aircraft Flight Test Center, Shanghai, 200120, China*

ABSTRACT
Based on the wide application of collaborative filtering algorithm in the current field of graduate employment, this paper introduces it into the employment recommendation mechanism of senior college students and takes it as one of the auxiliary means to formulate the employment policy for senior college students. By studying the implementation effect of employment policy, so as to explore the adaptability of employment policy. Through the time series prediction method based on neural network, the prediction model of employment policy adaptability of higher vocational tertiary students is constructed. Compare the prediction performance of this paper's prediction model with other models, predict the employment policy implementation effect through this paper's model, and finally, construct an evaluation system of employment policy prediction results to evaluate the model prediction results. The prediction fit of the model of this paper is 0.8644, and the average relative prediction error is 0.35%, which is the best performance among all prediction models. In the prediction of the employment of higher vocational college students in province A, the number of employment of higher vocational college graduates is positively correlated with the average annual income level and the market share of graduates, and negatively correlated with the total number of gaps between faculty and students in the institutions and the amount of education expenditure. The overall score of the employment policy implementation effect predicted by the prediction model in this paper is 88.8, which is a good evaluation result.

Keywords: collaborative filtering algorithm, neural network, time series, employment policy

1. Introduction

Graduates of higher vocational colleges and universities are an important part of social talent

✉ Corresponding author.
E-mail address: 1041315541@qq.com (Y. Chen).
Received 25 March 2024; Revised 05 June 2024; Accepted 15 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-491

resources, and also technical specialists urgently needed for national development. How to reform and improve the employment guidance work of graduates of higher vocational colleges and universities is a question that should be considered by the department of employment guidance for graduates of higher vocational colleges and universities and every educator [1-4]. In recent years, China's higher vocational education has clearly defined the policy of "service-oriented and employment-oriented", vigorously advocated the combination of work and study, and school-enterprise cooperation, and there has been a very promising situation in improving the employment rate [5-6]. However, due to the influence of traditional employment concept, many employers attach too much importance to academic qualifications and do not recognize higher vocational education, which makes the employment situation of graduates of higher vocational colleges and universities very serious, and the adaptation of employment policy can promote the employment of higher vocational colleges and universities students to a certain extent [7-9].

Employment policy refers to the various policy measures adopted by the state in the employment market, and its goal is to take effective measures to promote the healthy development of the employment market, promote social and economic development, protect the legitimate rights and interests of workers, promote social stability, and promote the economic development and social progress of the country [10-12]. In general, the contents of employment policy include the implementation of policies conducive to increasing employment opportunities, policies conducive to improving the quality of employment, policies conducive to stabilizing employment, policies conducive to high-quality employment, etc. Therefore, in the face of the national employment policy, with a proper understanding of and adaption to these employment policies, higher vocational and tertiary students are able to clarify the direction of their employment, and prepare for the employment [13-16].

Literature [17] explores the dynamics of job intentions and career adaptation. A survey of 251 school students was conducted and analyzed using Structural Equation Modeling and Hayes Process Macro unfolding. The results point out that job willingness directly affects employability, while career adaptation has an indirect effect on employability. It has realized practical significance for improving college students' employability. Literature [18] emphasizes the importance of occupational adaptability on the employment of graduates. The aim was to analyze individual differences in graduates' occupational adaptability and the impact of occupational adaptability on employment. A study was conducted on 183 graduates using a repeated measures design, and the results verified the positive correlation between the dimensions of occupational adaptability and determined the relationship between occupational adaptability and employability. Corresponding interventions are also proposed to improve the employability of graduates. Literature [19] describes an initial validation of the psychometric characteristics and factor structure of the CAAS, as well as an investigation of the relationship between employability skills and career adaptation. The findings pointed out that the CAAS can be used as a valid measure for assessing career adjustment skills. And the relationship between career adaptation and employability skills was found through CCA. Literature [20] outlined the relationship between employability skills and career adaptability through a study of UAE university students and advocated for more research to use boundary conditions to limit their effects on adaptive behavior. Literature [21] explored the employment situation of college students and emphasized the importance of career planning. By analyzing the current situation and influencing factors of college students' awareness of career planning, it points out its problems and reasons. It also puts forward initiatives such as building school-enterprise cooperation and internship training platforms, aiming to enhance college students' awareness of career planning and adaptability to the job market. Literature [22] aims to cultivate college students' proactive personality and career adaptability resources. Based on a randomized controlled trial, the "Staying Relevant" program was shown to be effective in facilitating a smooth transition from college to work. Literature [23] systematically introduces the vocational competence and adaptability of college students and emphasizes that with the development of big data technology, the relevance, accuracy and scientificity of teaching and education on college students' vocational adaptability are guaranteed in colleges and universities. Literature [24] based on the significance of adaptability to improve the model of psychological quality education, explored the psychological mechanism of adaptability cultivation, put forward a strategy for the cultivation of college students' adaptability, and introduced the cultivation objectives, contents and strategies at different stages. Literature [25] explored the mediating role of career adaptability and academic self-efficacy between hope, future work self and life satisfaction. A survey of 636 students yielded several conclusions that contribute to a systematic understanding of the factors affecting vocational students' life satisfaction and enrich the theoretical connotation of career adaptation.

In this paper, collaborative filtering algorithm is used to make personalized recommendations for the employment of higher vocational tertiary students, to improve the shortcomings of the employment policy, and to assist in the formulation and implementation of the employment policy. The effect of employment policy implementation is used as a replacement variable for the adaptability of employment policy, and the prediction model of the adaptability of employment policy for higher vocational college students is constructed through the time series prediction based on neural network. Compare the prediction performance of this paper's model with other popular prediction models (XGBoost, SVR, LSTM, RFR) to verify the prediction validity of this paper's model. After the specific case prediction of the implementation effect of employment policy, the evaluation system of the implementation effect of employment policy is constructed to evaluate the prediction results of this paper's model.

2. Employment policies based on collaborative filtering

2.1. Employment policy for students in higher education

The employment policy for college students is a series of policies and measures formulated by the state in order to promote the employment of college students, stabilize the employment situation in the society, and improve the comprehensive quality of college students, aiming at encouraging enterprises to absorb college students for employment, guiding and encouraging college students to go to the grass-roots level, the rural areas and remote areas for employment, promoting the vocational skills training and employment internship for college students, helping college students to start their own business, and establishing and perfecting the employment service system for college students. The implementation of these policies has helped to provide employment opportunities for college students. The implementation of these policies will help to provide university students with better employment opportunities and employment services, improve their employability and market competitiveness, and thus realize better employment and development.

2.2. Difficulties in the employment policy for students in higher education

The formulation of employment policies for students in higher education is one of the key links in solving the employment problem. However, in practice, there are some problems in the formulation of policies, such as unclear policy objectives, lack of pertinence of policy measures, and lack of scientific argumentation in the formulation of policies. This has led to poor implementation of policies and even deviations. First of all, the policy objective is not clear. The formulation of some college student employment policy lacks a clear goal, often only generally put forward to promote the employment of college students, but there is no specific indicators and standards to accurately measure the actual effect of the policy. This makes the policy implementation process lack of direction and focus, and can not effectively solve the actual problem. Secondly, the policy measures lack pertinence. Some college student employment policy lacks an in-depth understanding and analysis of market demand and the actual situation of college students, and the policy measures formulated are not targeted and effective.

Finally, the policy formulation lacks scientific evidence. The formulation of some college student employment policy lacks scientific proof and evaluation, and does not fully consider the feasibility and implementation effect of the policy. This leads to a variety of problems in the implementation of the policy, such as the difficulty of policy implementation, the policy effect is not significant. Therefore, policymakers need to conduct in-depth research and analysis before formulating policies, and fully consider various factors to ensure the scientificity and feasibility of policies.

2.3. Student employment recommendation based on collaborative filtering algorithm

Through the study of the previous college student employment policy and its dilemma, this section proposes a student employment recommendation method based on collaborative filtering algorithms to solve the problems in student employment, to improve the college student employment policy and to assist in the formulation and implementation of the college student employment policy.

Collaborative filtering algorithms are generally used to calculate the distance between users using their historical information, and then assign the product ratings of the target user's neighboring users to predict the target user's preference for a specific product in order to achieve the recommendation results. Collaborative filtering algorithms can be classified into user-based CF and item-based CF [26-27]. User-based collaborative filtering predicts the ratings of similar target users based on their inter-user rating behaviors, and is suitable for scenarios with fewer, more real-time, and more social users. Item-based collaborative filtering predicts user ratings based on the similarity between the predicted item and the actual item selected by the user, and the user's new behavior leads to real-time changes in the recommendation results, which is suitable for areas with strong personalization needs.

In this paper, a collaborative filtering algorithm is used to design a student employment recommendation mechanism to provide employment recommendations for high school and college students, in order to assist in the development and implementation of employment policies related to high school and college students.

Crawler technology is used to collect the information of enterprises' job openings and past job seekers, extract the eigenvalues and normalize them, and calculate the similarity between graduates and enterprise units t based on the similarity between graduate X and job seeker Y. On the basis of the similarity between graduate X and enterprise t, the heat of job seeking of enterprise is calculated according to the algorithm of random walk model. Finally, we calculate the final ranked comprehensive weights to complete the employment recommendation based on collaborative filtering.

In this process, assuming that the feature base of student A is $T_a = \{S_1, S_2, ..., S_i\}$, and the feature base of a position in recruiting company B is $T_e = \{Q_1, Q_2, ..., Q_j\}$, the feature base text is converted into the form of vocabulary by a lexical algorithm, where the feature base is a collection of texts describing an object. Then the feature library vocabulary is subjected to exact pattern segmentation, finding the maximum probability path based on dynamic programming to find the maximum cut combination based on word frequency, and predicting the segmentation based on HMM model. Through the above word separation process for feature libraries T_a and T_e, the following two formulas are obtained, the processing formula for feature library T_a is shown in Eq. (1), and the processing formula for feature library T_e is shown in Eq. (2):

$$F_a = jieba\_cut(T_a, HMM = True) = \{W_{a1}, W_{a2}, \cdots, W_{am}\} \tag{1}$$

$$F_e = jieba\_cut(T_e, HMM = True) = \{W_{e1}, W_{e2}, \cdots, W_{en}\} \tag{2}$$

where m denotes the number of participles of F_a, n denotes the number of participles of F_e, W_{am} is the word set obtained after participles of T_a for the feature library of student A, and W_{en} is the word set obtained after participles of T_e for the job feature library of enterprise B. Then all the above student and job information sub-phrase results are concatenated to get the word pooling, and the word pooling formula is shown in equation (3):

$$I_k = \bigcup_{u=1}^{m} w_{au} \bigcup_{v=1}^{n} w_{ev} \tag{3}$$

where, $u \in \{1,2,\ldots,m\}$, $v \in \{1,2,\ldots,n\}$, I_k are the word pools of students A and enterprises B.

Finally, the word collection I_k, student participle Fa and recruitment job participle Fe are subjected to text classification and word frequency statistics according to the frequency of occurrence, and the feature library of student A and recruitment job is converted into word frequency vectors. The text categorization and frequency statistics methods are performed based on the plain Bayesian model, and the specific process includes:

It is known that the "simplicity point" of the plain Bayes lies in the assumption that each feature is independent of each other, i.e., any participle is independent of each other, and the word frequency statistics are obtained to derive the word frequency vector of the Ta and Te feature libraries, the formula is shown in Equation (4):

$$x = \{F_{a1}, F_{a2}, \cdots, F_{am}\}, y = \{F_{e1}, F_{e2}, \cdots, F_{en}\} \tag{4}$$

where F_{am} is the number of occurrences of W_{em} and F_{en} is the number of occurrences of w_{en}.

In the process of calculating the similarity of graduates and enterprises, firstly, the similarity of specified graduates X and previous job seekers Y is calculated, each job seeker and enterprise corresponds to each other, and graduates and previous job seekers whose similarity is close to each other are considered to be in a set of their job seeking needs, then the similarity calculation formula of X and Y is shown in Equation (5):

$$sim\_stu(x,y) = \sum_{i=1}^{k} M_i(x,y) * \sigma_i + e^{\beta-(t_x-t_y)} \tag{5}$$

where, i is the graduate analysis model feature value, when i takes the value of 5, it represents the school achievement, political profile, province, gender and major feature value. If the feature attributes in the ith dimension of vectors x and y are the same, then $M_i(x,y)=1$ and vice versa is 0. σ_i represents the weight of the feature attributes in the ith dimension. As time passes, the similarity of the information of previous job seekers is less meaningful for the reference of graduates, t_x and t_y represent the graduation time of graduates x and previous job seekers y respectively, and β is the coefficient of the influence of time decay.

The formula for calculating the similarity of x and τ is shown in equation (6):

$$sim\_ent(x,\tau) = \frac{1}{|N(\tau)|} * \sum_{j \in N(\tau)} simstu(x,j) + N(\tau) * \varphi \tag{6}$$

where $N(\tau)$ represents the set of previous job seekers contracted by enterprise τ, $|N(\tau)|$ is the total number of previous job seekers contracted, and φ is the coefficient of influence of the number of people contracted by enterprise τ.

Through the above steps can be obtained M graduates $\{x_1, x_2, \ldots, x_{M-1}, x_M\}$, and N business units $\{y_1, y_2, \ldots, y_{N-1}, y_N\}$ similarity composition $M \times N$ matrix.

The process of calculating the heat of job seeking of enterprises is as follows:

1) Normalize the information extracted from the job postings of enterprises.

2) According to the random walk model algorithm, the enterprise is taken as the vertex of the undirected graph, and the similarity of the eigenvalues between the two vertices is taken as the weight of the edges E, then the constructed weighted undirected graphs $G(V,E)$ and V_i represent the vertices of the undirected graph, and the weight $E(h,i)$ represents the similarity of the vertices V_h

and V_i.

3) According to the Page Rank algorithm and the random walk model in Figure $G(V,E)$ along each node randomly walking, then get the weight value $E(h,i)$ calculation formula as shown in equation (7):

$$
\begin{aligned}
E(h,i) = \gamma_1^* \frac{|F1_h \cap F1_i|}{|F1_h \cup F1_i|} + \gamma_2 * \frac{|F2_h \cap F2_i|}{|F2_h \cup F2_i|} + \gamma_3 * \frac{|F3_h \cap F3_i|}{|F3_h \cup F3_i|} \\
+ \gamma_4 * \frac{|F4_h \cap F4_i|}{|F4_h \cup F4_i|} + \gamma_5 * \frac{|F5_h \cap F5_i|}{|F5_h \cup F5_i|}
\end{aligned}
\tag{7}
$$

where, in the above equation, F1F4 denotes the set of four types of eigenvalues of enterprises engaging in industry, working city, recruiting specialty, recruiting education and nature of enterprise, and $\gamma_1 \sim \gamma_5$ denotes the weight coefficients of the five types of eigenvalues in the similarity calculation, respectively:

4) The calculation of job seeking hotness of enterprise τ corresponding to node V_r is shown in equation (8):

$$
nt\_hot(\tau) = 1 + \left(\sum_{j \in V(\tau)} \frac{ent\_hot(j)}{|V(j)|} - 1 \right) * \rho \tag{8}
$$

where, ρ is the coefficient constant, $V(\tau)$ and $V(j)$ denote the sets pointing to nodes τ and j respectively, that is, the degree of the nodes in the graph, since Figure G is an undirected graph, the out degree and in degree of each node are equal, that is to say, we get the hotness of the enterprise's job search.

The process of calculating the sorted composite weights is as follows:

Algorithm $sim\_value(x,\tau)$ is used to calculate the final sorting comprehensive weights as the reference index for employment recommendation, and the weight calculation formula is shown in equation (9):

$$
\begin{aligned}
sim\_value(x,\tau) = \varepsilon * sim\_ent(x,\tau) \\
+ (1-\varepsilon) * \frac{ent\_hot(\tau)}{\max_{\mu \in A}(ent\_hot(\mu))}
\end{aligned}
\tag{9}
$$

In the above equation, ε is the coefficient parameter and A is the set of firms.

3. Forecasting model for the effects of the implementation of the employment policy

In the previous chapter, this paper constructed the employment policy for college students based on collaborative filtering, and the adaptability of the employment policy is investigated in this chapter. The employment policy implementation effect is taken as a replacement variable for the adaptability of the employment policy, and the prediction model of the implementation effect of the employment policy is constructed, so as to explore the adaptability of the employment policy based on collaborative filtering in the previous paper.

3.1. *Policy implementation*

Policy implementation refers to the process by which policy implementers translate the conceptualization of policy content into practical results through the construction of organizational structures, the use of various political resources, the adoption of various methods, coordination and control, and other actions, so as to achieve the goals set out in the policy.

Policy implementation is the behavioral process of combining various means and methods in order to achieve the goals of policy formulation. It is a policy activity that transforms a formal policy program into actual results. The content of this kind of behavior has two main aspects: one is to transform the relatively virtual policy decisions into the actual process of operation, and the other is a process of continuous improvement of the policy implementation environment according to the goals set out in the political decision-making. It is characterized by implementation, targeting, creativity, compulsion, pragmatism, and time. It consists of seven main steps, namely, policy promotion, plan formulation, organization and implementation, policy piloting, full implementation, coordination and control, and tracking of decisions.

Policy implementation is an important stage in the whole policy process, which is the key to the success or failure of policy formulation. Whether the policy can be effectively implemented in reality is the touchstone of the success or failure of policy formulation, so it has a crucial status and role in policy activities. On the one hand, policy formulation is the only way to transform political goals into reality. A correct policy program is designed to influence reality to a certain extent, and to achieve this it is necessary to rely on effective policy implementation. Without accurate and efficient policy implementation, even the best policy programs are just words on paper, and the goals for which the policies were formulated cannot be realized. On the other hand, policy implementation is the only criterion for testing whether a policy is correct or not. The correctness or otherwise of a policy must ultimately be tested by practice.

3.2. Neural network based time series forecasting

The purpose of time analysis is to describe the change law between a certain sequence and other related sequences or factors from a dynamic point of view, and to extract as much information as possible from these change laws for predicting the future value of the sequence. However, for nonlinear time series, the traditional time series model is difficult to find an appropriate parameter estimation method, and neural network can automatically approach the best fitting function to the sample data law through the self-learning process, with good nonlinear mapping ability, in the establishment of nonlinear time prediction model is more effective.

1) BP neural network model. BP neural network is a multilayer forward-oriented network with an error back-propagation algorithm [28-29]. BP neural network can approximate any continuous function with arbitrary accuracy, so it is widely used for modeling and identification of nonlinear systems. It includes input layer, hidden layer and output layer, each layer consists of several neurons, and there is no coupling between neurons in the same layer.

2) Learning algorithm of BP neural network. The idea behind the derivation of the BP neural network guided learning formula is to correct the network weights and thresholds while making the error function (E) decrease along the negative gradient direction. The standard mean square error function is used for the error function:

$$E = \frac{1}{2}\sum_{l}\left(T_l - Z_l\right)^2 \tag{10}$$

The three layers of BP neural network nodes are represented as: input layer node X_j, hidden layer node Y_i, output layer node Z_l. The weight between input node and hidden node is W_{ij}, the weight between hidden node and output node is W_{li}, the threshold of hidden layer is θ_i, and the threshold of output layer is θ_l. The learning process of the BP network is as follows when the desired output of the output node is T_l:

(1) Initialize the network structure. Set the initial weights and thresholds of the network so that they are uniformly distributed smaller random numbers to ensure that the network works in the region

where the activation function changes are sensitive. Set the error function E, given the computational accuracy ε and the maximum number of iterations M.

(2) Calculation of the forward propagation process of information. Input p sample pairs $\left(X^P, Y^P\right)$, $P = 1, 2, \cdots k$. Calculate the output values of the hidden and output nodes according to the following equation:

$$\begin{cases} Y_j = f\left(\sum_i W_{ji} X_i - \theta_j\right) \\ Z_i = f\left(\sum_j W_{ij} Y_j - \theta_i\right) \end{cases} \tag{11}$$

(3) Calculation of error back propagation. When the error between the output response and the desired output does not meet the pre-set requirements, it is transferred to the error back propagation calculation. Calculate the error of input nodes and hidden nodes according to the following equation:

$$\begin{cases} \dfrac{\partial E}{\partial W_{li}} = -\delta_l Y_i \\ \dfrac{\partial E}{\partial W_{ij}} = \delta_i X_j \end{cases} \tag{12}$$

$$\begin{cases} \delta_l = -\left(T_l - Z_l\right) \times f'\left(\sum_i T_{li} Y_i - \theta_l\right) \\ \delta_i = f'\left(\sum_j W_{ij} X_j - \theta_i\right) \times \sum_l \delta_l T_{li} \end{cases} \tag{13}$$

After calculating the equivalent errors δ_l and δ_i of the neurons in each layer, return to step 2 and perform forward propagation calculations and error back propagation for the other learning sample pairs as well until all learning samples have been calculated.

(4) Adjust the weights and thresholds of each connection layer. Correct the connection weights and thresholds layer by layer from the output layer through each intermediate layer according to the direction of reducing the target output and the actual error. Correct the weights and thresholds of the hidden layer nodes to the output layer nodes according to the following formula:

$$W_{ii}\left(k+1\right) = W_{li}\left(k\right) + \Delta W_{li} = W_{li}\left(k\right) + \eta \delta_l Y_i \tag{14}$$

$$\theta_l\left(k+1\right) = \theta_l\left(k\right) + \eta \delta_l \tag{15}$$

Correct the weights and thresholds from the input layer nodes to the hidden layer nodes according to the following equation:

$$W_{ij}\left(k+1\right) = W_{ij}\left(k\right) + \Delta W_{ij} = W_{ij}\left(k\right) + \eta \delta_i X_j \tag{16}$$

$$\theta_i\left(k+1\right) = \theta_i\left(k\right) + \eta \delta_i \tag{17}$$

where η is the learning rate.

(5) Calculate the global error. i.e:

$$E = \sum_{p=1}^{k} e_k < \varepsilon \tag{18}$$

$$e_k = \sum_{l=1}^{n} \left| T_l^{(p)} - Z_l^{(p)} \right| \tag{19}$$

Determine whether the network error meets the requirements. When the error reaches the preset accuracy $(E < \varepsilon)$ or the number of iterations is less than the set maximum number of iterations $(m < M)$, end the algorithm. Otherwise, select the next learning sample and the corresponding desired output, and return to step 2 for a new round of learning until $E < \varepsilon$ is satisfied.

3) BP neural network integration model. The input variables of a BP neural network are the endogenous variables of a system to be analyzed, which are generally determined based on professional knowledge and practical problems. The output variable is usually the exogenous variable of the system to be analyzed, i.e., the target function to be achieved by the system model, which can be one or more, and its selection is relatively easy. A time series forecast is the value of the variable to be predicted at some point or points in the future. For the selection of input variables, the idea of integrating econometrics with BP neural networks is proposed in this paper for the time series variable forecasting problem of this study. Considering the principle of forecasting, the factors affecting the future value of the output variable are multifaceted, which not only need to be extrapolated based on the demand development trend embodied in the historical data series of the variable itself, but also need to be adjusted continuously according to the changes of its input variable and its relationship with the dependent variable. The input variables should not only be detected and extracted, but also determine how many past observations are more appropriate to be selected as inputs to the prediction network. After reasonably determining the input and output variables of the BP neural network, the BP neural network can be utilized for its good nonlinear mapping ability, and through the self-learning process of the sample data, it can automatically approximate the functions that portray the laws of the sample data, and through the effective control of the input variables, it can achieve the effective control and prediction of the output variables, and it can achieve a better effect for the time series prediction problem.

4. Analysis of employment policy projections

Starting from the implementation effect of employment policy, this paper explores in turn the performance and prediction results of this paper's model on the adaptability of employment policy.

4.1. Comparison of predicted performance

This paper synthesizes multiple influencing factors such as economic, social, policy, demographic, educational level and industry category. By comprehensively analyzing these influencing factors, the complex relationship between them and employment policy adaptability is captured to improve the accuracy of fitting and prediction. In order to explore the prediction performance of the model in this paper, the prediction model in this paper is compared with other classical prediction models (XGBoost, SVR, LSTM, RFR). In order to compare the fitting effects of different models, the RMSE, MAE and R^2 of each model are calculated respectively, and the comparison results are shown in Table 1.

As can be seen from Table 1, when predicting employment policy adaptability, it is found by comparing with XGBoost, SVR, LSTM and Random Forest Regression model that using the prediction model in this paper to fit the data on employment policy adaptability can obtain the best fitting result (0.8644), provide more accurate and reliable prediction results, and help to analyze the prediction of employment policy adaptability in depth.

Table 1. Comparison of prediction results of different methods

Prediction method	RMSE	MAE	R^2

XGBoost	0.0265	0.0296	0.7945
SVR	0.0358	0.0304	0.7418
LSTM	0.0374	0.0327	0.7253
RFR	0.0326	0.0312	0.7094
Ours	0.0105	0.0147	0.8644

The forecasting performance of the model of this paper is further examined in terms of the absolute and relative errors of the forecasting results. Taking Province A as an example, the number of new jobs is used as a replacement variable to measure the adaptability of employment policies, and its employment data from 2014 to 2020 are modeled and predicted, and the prediction results of the different models are summarized, and the fitting results are shown in Table 2.

The average relative prediction error of the prediction model in this paper is 0.35%, the prediction effect is very satisfactory, which is lower than the average relative prediction error of both the time series prediction and the gray prediction, so the combined prediction is better than the prediction effect of the XGBoost, SVR, LSTM and RFR models.

Table 2. Prediction results and absolute and relative error of different methods

Year		2014	2015	2016	2017	2018	2019	2020
Real value		15.68	14.85	18.44	20.73	12.36	13.84	14.06
Ours	Predict value	15.62	14.79	18.46	20.79	12.41	13.89	13.99
	Absolute error	0.06	0.06	0.02	0.06	0.05	0.05	0.07
	Relative error	0.38%	0.40%	0.11%	0.29%	0.40%	0.36%	0.50%
XGBoost	Predict value	15.26	14.02	18.95	21.37	12.86	14.28	13.59
	Absolute error	0.42	0.83	0.51	0.64	0.50	0.44	0.47
	Relative error	2.68%	5.59%	2.77%	3.09%	4.05%	3.18%	3.34%
SVR	Predict value	14.95	14.25	19.06	21.65	12.87	14.64	14.85
	Absolute error	0.73	0.60	0.62	0.92	0.51	0.80	0.79
	Relative error	4.66%	4.04%	3.36%	4.44%	4.13%	5.78%	5.62%
LSTM	Predict value	16.82	15.64	17.86	19.85	13.67	14.56	15.07
	Absolute error	1.14	0.79	0.58	0.88	1.31	0.72	1.01
	Relative error	7.27%	5.32%	3.15%	4.25%	10.60%	5.20%	7.18%
RFR	Predict value	14.87	14.15	18.03	20.22	12.88	14.37	14.69
	Absolute error	0.81	0.70	0.41	0.51	0.52	0.53	0.63
	Relative error	5.17%	4.71%	2.22%	2.46%	4.21%	3.83%	4.48%

4.2. Forecast analysis of the effects of the implementation of the employment policy

In order to verify the effect of the implementation of employment policy on the employment level of graduates of higher vocational colleges and universities, with reference to the method of econometric research, this paper selects the annual data from 2003 to 2012, and in order to eliminate the instability of the data and to ensure the consistency of the data, the relevant data variables are processed using logarithmic series.

The number of college graduates employed (Emp) is used as the explanatory variable, the employment gap of professional and technical personnel (Tec), the average annual income level of employed personnel (Y), the number of students enrolled in higher vocational colleges and universities (Rec), the number of graduates from higher vocational colleges and universities (Gra), the total number of gaps between teachers and students (Staff), the number of graduates from higher vocational colleges and universities per 100,000 population (Gra1), and the annual investment in education (Fund) are used as the explanatory variables to set up the annual education budget (Tec). Fund) as explanatory variables and set up an econometric model as shown in (20):

$$Empt = C + \beta 1Tect + \beta 2Yt + \beta 3Rect + \beta 4Grat + \beta 5Staff + \beta 6Gra1t + \beta 7Fundt + \varepsilon t \tag{20}$$

where t represents the year and εt is the residual term. The data were used for regression analysis of the original equation (20), and the variables were screened according to the explanatory power of the model and the regression results, and the final regression estimates are shown in Table 3.

Firstly, it can be seen from the sample regression results that the R^2 is 0.99, that is, the variables selected by the model can fully reflect the change trend of the explanatory variables. The regression results are generally significant through the F-statistic: the average annual employment income level (Y), the total number of teacher-student gaps in schools and colleges (Staff), the market factors in education expenditure (Fund) and the number of graduates of colleges and universities per 100,000 employed people (Gra1) are 2.38, -2.77, 8.99 and -0.60, respectively, and the corresponding concomitant probabilities are 0.0734, 0.0482, 0.0006 and 0.5426 (However, the variable standard is incorrectly 0.0741, so it also has a significant impact on the explanatory variable), indicating that the average annual employment income level (Y) is at a significance level of 10%, and the total number of teacher-student gaps (Staff) and market factors have a significant impact on the employment number of graduates of higher vocational colleges in province A at a significance level of 5%.

Secondly, it can be seen from the regression results that there is a positive correlation between the employment number of graduates of higher vocational colleges and universities in province A and the average annual income level of employment and the share of graduates in the market, that is to say, if other influencing conditions remain unchanged, for every 1% increase in the average annual income level, the growth rate of the number of graduates of higher vocational colleges and universities in province A is increased by 0.232 percentage points. For every 1% increase in the market share of graduates, the growth rate of the number of employed senior college graduates in Province A increases by 1.165 percentage points. And there is an inverse correlation between the employment number of higher vocational and post-secondary graduates in Province A and the total number of teacher-student gaps and the investment in education funding, i.e., for every 1% increase in the total number of teacher-student gaps in the institutions, the employment number of higher vocational and post-secondary graduates in Province A decreases by about 0.367 percentage points, all other influencing conditions being unchanged. For every 1 percent increase in the amount of education funding, the number of employed senior college graduates in province A will decrease by about 0.045 percentage points.

Table 3. Sample regression analysis results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.354859	0.924415	6.710352	0.0023
Y	0.231544	0.090487	2.384795	0.0734
STAFF	-0.367452	0.124745	-2.768954	0.0482
GRA1	1.164698	0.132254	8.987458	0.0006
FUND	-0.045278	0.074084	-0.604872	0.5426
R-squared	0.999745	Mean dependent var		12.624854
Adjusted R^2	0.998245	S.D. dependent var		0.205462
S.E. of regression	0.007854	Akaike info criterion		-6.525746
Sum squared resid	0.000236	Schwarz criterion		-6.412163
Log likelihood	34.364852	Hannan-Quinn criter.		-6.754854
F-statistic	1542.384	Durbin-Watson stat		2.594851
Prob (F-statistic)	0.000001			

4.3. Evaluation of the projected effects of employment policy implementation

4.3.1. Construction of a system for evaluating the effectiveness of employment policy implementation. The author further consults and understands with the staff of the Employment Guidance Center of Colleges and Universities in Province A, the staff of the Employment Promotion Association, and the teachers of the employment guidance departments of colleges and universities and their sister colleges and universities, under the guidance of the instructor, accurately locates the deeper connotations of the indicators and the standards of measurement, improves the indicators containing each other, duplicating connotations, and making it difficult to obtain data in the initial selection of the indicators, and further analyzes the scientificity of the indicators, systematic and operability, synthesize the application and research of most scholars, consider the actual situation of the implementation of employment promotion policy in private universities in Guangdong Province, and remove the irrelevant and repetitive indicators so that they are applicable to the research purpose of the thesis. After modification and continuous optimization, the index system for evaluating the implementation effect of the employment policy is screened and established, and the weights are calculated, and the results are shown in Table 4.

Table 4. Employment policy implementation effect evaluation index system

Target layer	Primary index	Weight	Secondary index	Weight
Employment policy implementation effect (A)	Policy benefit (B1)	0.346	Macroscopic benefit (C1)	0.500
			Microscopic benefit (C2)	0.500
	Policy efficiency (B2)	0.337	Policy publicity (C3)	0.264
			Policy application procedure (C4)	0.223
			Policy service cycle (C5)	0.245
			Policy implementation (C6)	0.268
	Policy response (B3)	0.317	Respond to social needs (C7)	0.231
			Respond to graduate needs (C8)	0.286
			Implementation satisfaction (C9)	0.226
			Policy satisfaction (C10)	0.257

4.3.2. Evaluation of forecast results. Based on the employment policy implementation evaluation index system to make questionnaires, to predict the employment policy implementation effect in 2021, and distribute questionnaires to evaluate the employment policy implementation prediction effect of this paper. The questionnaire data are collected and summarized, and the evaluation of employment policy implementation prediction results is organized as shown in Table 5.

As can be seen from Table 5, the evaluation score of the employment policy implementation effect in 2021 predicted by the prediction model of this paper is 88.8, and the best performance in the first-level indicators is the policy efficiency (91.1), followed by the policy responsiveness (88.9), and the last is the policy effectiveness (86.5). The scores of the secondary indicators are between [86, 94]. It can be seen that this paper's model to predict the results of the implementation of employment policies for higher education tertiary students has received a good evaluation.

Table 5. Employment policy implementation predict effect evaluation results

Target layer	Score	Primary index	Score	Secondary index	Score
Employment policy implementation effect (A)	88.8	Policy benefit (B1)	86.5	Macroscopic benefit (C1)	87
				Microscopic benefit (C2)	86
		Policy efficiency (B2)	91.1	Policy publicity (C3)	92
				Policy application procedure (C4)	90
				Policy service cycle (C5)	88
				Policy implementation (C6)	94
		Policy response (B3)	88.9	Respond to social needs (C7)	86
				Respond to graduate needs (C8)	90
				Implementation satisfaction (C9)	88
				Policy satisfaction (C10)	91

5. Conclusion

In this paper, a collaborative filtering algorithm is used to make employment recommendations for high school and college students, and this is used as an aid in the development of employment policies. It explores the adaptability of the employment policy by predicting the implementation effect of the employment policy. Study the prediction performance, prediction results and evaluation of prediction results of the employment policy adaptability prediction model to explore the adaptability of the employment policy for higher vocational tertiary students.

Comparing the prediction performance of this paper's model with XGBoost, SVR, LSTM and random forest regression model, the prediction results of this paper's prediction model have the highest goodness of fit of 0.8644 and the smallest average relative prediction error of 0.35%.

In the prediction of the employment of high school and college students in Province A, the growth rate of the number of high school and college graduates employed in Province A increased by 0.232 and 1.165 percentage points for every 1% increase in the average annual income level and the number of graduates occupying the market, respectively. For every 1% growth in the total number of teacher-student gaps in institutions and the amount of education spending, the employment number of higher vocational and post-secondary graduates in Province A will decrease by about 0.367 and 0.045 percentage points, respectively.

The evaluation score of the effectiveness of employment policy implementation predicted by the prediction model in this paper is 88.8, and the score of the first-level indicator is in the interval of [86.5, 91.1], with the best performance being policy efficiency and the worst being policy effectiveness. The scores of the secondary indicators are in the range of [86, 94].

References

[1] Tan, J. (2023). Research on Employment Survey of Vocational College Graduates. International Journal of Education and Humanities, 11(3), 276-286.

[2] Torun, H., & Tumen, S. (2019). Do vocational high school graduates have better employment outcomes than general high school graduates?. International Journal of Manpower, 40(8), 1364-1388.

[3] Cherednichenko, G. (2020). Employment and labor market outcomes of college and vocational school graduates. Voprosy obrazovaniya/Educational Studies Moscow, (1), 256-282.

[4] Jaafar, S. N., Zakaria, N., & Abd Rasheid, N. (2018, July). Career choice and employability skills for vocational college students. In Journal of Physics: Conference Series (Vol. 1049, No. 1, p. 012050). IOP Publishing.

[5] Foong, L. M., & Zheng, J. H. (2024). Employment Competency of Graduates from Higher Vocational Colleges and Universities Based on the Perspective of Enterprises' Needs Empirical Analysis. Online Journal for TVET Practitioners, 9(2), 98-105.

[6] You, M., & Yin, J. (2024). Analysis of the Current Situation of Employment Satisfaction of Graduates in Higher Vocational Colleges and Universities. In SHS Web of Conferences (Vol. 190, p. 03009). EDP Sciences.

[7] Yu, F., & Lu, R. (2022). Analysis of the Employment Status and Countermeasures of Medical Graduates in Frontier Vocational Colleges in the Post-Epidemic Era: Take X Vocational and Technical College as an Example. Journal of Sociology and Ethnology, 4(7), 30-35.

[8] Po, Y., Jianru, G., & Yinan, J. (2015). Analysis of Employment Quality of Chinese Vocational and Technical College Graduates. Chinese Education & Society, 48(1), 1-22.

[9] Chen, Y. (2024). A Survey and Research on the Employment Awareness of Vocational College Students. Academic Journal of Humanities & Social Sciences, 7(1), 36-43.

[10] Rhodes, M. (2015). Employment policy. Policy-making in the European Union, 293-318.

[11] Harvey, P. (2014). Securing the right to employment: Social welfare policy and the unemployed in the United States (Vol. 1030). Princeton University Press.

[12] Mucciaroni, G. (2023). The Political Failure of Employment Policy, 1945–1982. University of Pittsburgh Press.

[13] Immervoll, H., & Scarpetta, S. (2012). Activation and employment support policies in OECD countries. An overview of current approaches. IZA Journal of Labor Policy, 1, 1-20.

[14] French, E., & Strachan, G. (2015). Women at work! Evaluating equal employment policies and outcomes

in construction. Equality, Diversity and Inclusion: An International Journal, 34(3), 227-243.

[15] Piasna, A., Burchell, B., & Sehnbruch, K. (2019). Job quality in European employment policy: one step forward, two steps back?. Transfer: European Review of Labour and Research, 25(2), 165-180.

[16] Ko, H., & Cho, H. (2017). Revisiting the effectiveness of the employment-oriented welfare state: Considering the quality of employment achievement. Asian social work and policy review, 11(2), 158-167.

[17] Kwon, J. E. (2019). Work volition and career adaptability as predictors of employability: Examining a moderated mediating process. Sustainability, 11(24), 7089.

[18] Monteiro, S., Taveira, M. D. C., & Almeida, L. (2019). Career adaptability and university-to-work transition: Effects on graduates' employment status. Education+ Training, 61(9), 1187-1199.

[19] de Guzman, A. B., & Choi, K. O. (2013). The relations of employability skills to career adaptability among technical school students. Journal of Vocational Behavior, 82(3), 199-207.

[20] Khalid, K., & Ahmad, A. M. (2021). The relationship between employability skills and career adaptability: A case of undergraduate students of the United Arab Emirates. Higher Education, Skills and Work-Based Learning, 11(5), 1035-1054.

[21] Chen, C. (2024). Cultivation of University Students' Career Planning Consciousness and Adaptability of Employment Market. Advances in Vocational and Technical Education, 6(5), 185-190.

[22] Green, Z. A., Noor, U., & Hashemi, M. N. (2020). Furthering proactivity and career adaptability among university students: Test of intervention. Journal of Career Assessment, 28(3), 402-424.

[23] Yan, X. (2024). Research on the Strategies for Improving College Students' Career Adaptability from the Perspective of Big Data. Frontiers in Educational Research, 7(1).

[24] Xiao, F., Hua, W., Han, J., & Yan, R. (2020). A preliminary study on adaptability of college students in the new era and its cultivating model. Psychology, 11(12), 2055-2065.

[25] Zeng, Q., He, Y., Li, J., Liang, Z., Zhang, M., Yi, D., & Quan, J. (2022). Hope, future work self and life satisfaction among vocational high school students in China: The roles of career adaptability and academic self-efficacy. Personality and Individual Differences, 199, 111822.

[26] Yu Sun & Qicheng Liu. (2024). Collaborative filtering recommendation based on K-nearest neighbor and non-negative matrix factorization algorithm. The Journal of Supercomputing(1),79-79.

[27] Nidhi Asthana & Haewon Byeon. (2024). U-Net-based Recommender Systems for Political Election System using Collaborative Filtering Algorithms. Journal of information and communication convergence engineering(1).

[28] Lianying Zhang,Jiaquan Shan,Qian Bai,Zhaoxin Zhang,Siyuan Zhang,Xin Cui & Xiaohu Yang. (2024). Energy efficiency prediction of refrigerating station system based on BP neural network and optimization of operating strategy. Journal of Building Engineering111182-111182.

[29] Shanqiang Fu,Mengjuan Liu,Han Wu,Xin Liang & Xiaohui Zeng. (2024). Active disturbance rejection control based on BP neural network for suspension system of electromagnetic suspension vehicle. International Journal of Dynamics and Control(1),1-13.