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Research on analysis and prediction model of development trend of private higher vocational colleges and universities based on deep learning

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SUMMARY: *The research develops an eight-dimensional framework based on four dimensions, namely, financial resources of education, socio-economic conditions, the wider social context, and properties of the student population. The variables studied are spending on higher vocational education, expenditure per student, GDP, level of household spending, overall retail sales of consumer products, the urban unemployment rate, population size, and the number of secondary school graduates. Grey relational analysis is used to identify those factors that have the strongest relationship with the trends in enrollment in a private higher vocational education. Based on these results, the paper incorporates the outcomes into a BP neural network and the GM(1,1) model, overcoming the natural shortcomings of a stand-alone GM(1,1) forecast by developing a combined prediction model of GM-BP. This structure is then used to predict the size of the private higher vocational education sector between 2025 and 2035, as well as the expected changes in the volume of enrollment and the disciplinary mix during this period. The findings show that the total enrollment of students within the private higher vocational institutions will peak at 946,062 in 2035, and the fields of transportation, medicine, and healthcare are the ones that will attract the largest proportion of students.*

KEYWORDS: *gray correlation model; GM (1,1) model; GM-BP model; trend prediction; private higher education*

1 Introduction

Nearly 14 years after being revised, the Vocational Education Law of the People’s Republic of China was finally implemented on May 1, 2022. Its implementation will offer a stronger legal basis to address the old challenges in the vocational education reform and practice and will also set a more predictable and more organized path to the future of the industry. Since the early history of vocational education in China, higher vocational schools and universities have been important social agencies because they produced large numbers of very skilled workers, and different kinds of school sponsors had been involved in organizing and delivering vocational education. This situation led to the emergence, expansion, and integration of the private higher vocational institutions into the vocational education environment. This increase is part of a larger belief that social advancement is based on talent development and it is evident that these institutions do not operate as mere extra providers but are a component of the overall private vocational education system [1]. The organizational framework of the sector has become more diversified, enhancing its ability to meet changing social demands. Over time the supply system of higher vocational education has also expanded significantly, and it has

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contributed greatly to the structural transformation of higher education systems across the world and the increased accessibility to tertiary studies[2-4].

The emergence of the digital economy, industrial upgrading, and the increased pace of regionalization have transformed the technical and skilled labor demand in a fundamental manner and created the new opportunities and significant challenges before the private higher vocational institutions [5-7]. In comparison to most other kinds of institutions, these schools have more freedom in changing their disciplinary offerings to suit the industrial structure of the region and hence offer a stable talent pipeline to local economies. Meanwhile, new technologies like artificial intelligence, big data, and 5G are facilitating the informatization and digitalization of education, changing the nature of instructional materials and methods of instruction, and creating novel models of vocational education able to support development of high quality [8-12]. In addition to better resource allocation, these technologies enhance the effectiveness of data-driven assessment and productivity of educational management. Deep learning as a major subdivision of artificial intelligence has especially high potential in improving decision-making in vocational education through the mining and analysis of educational data, which allows making more exact and focused decisions [13, 14]. It is thus appropriate and urgent to analyze both in a systematic way the trajectory of development of private higher vocational institutions considering the joint impact of policy support, industrial restructuring and technological changes, and to build analytical and predictive models based on deep learning to be used in guiding the reform process, planning strategies and long-term growth.

In this paper, the author uses a grey relational analysis to determine the main determinants of the development of the private higher vocational institutions. The method of grey relational analysis is used to measure the intensity of the relationship between private higher vocational enrolment and various other related factors such as spending on higher vocational education. The framework is also combined with a BP neural network to enhance the accuracy of predictions. Based on the trend of higher vocational education over the past 33 years (since the beginning of 1992) and the major forces behind it, the GM-BP model can be used to predict the scale of enrollment and the number of students in the private higher vocational institutions during the period of 2025-2035, which is a more credible foundation to predict future tendencies. In order to reflect possible changes in the disciplinary structure of private higher vocational education, input variables include the output shares of the primary, secondary and tertiary sectors in the national economy, along with the main categories most closely related to each sector, and these variables are entered into the DPS Data Processing System to predict structural changes in private higher vocational programs.

2 Design of a model for predicting the development trend of private higher vocational colleges and universities

2.1 Data sources

The research predicts the further growth of private higher vocational schools between the years 2025 and 2035 using the past 33 years of trends in higher vocational education since 1992. Considering the fact that the key determinants may take some time to exert their impact on higher vocational institutions instead of affecting them right away, the focus of the analysis is on the figures of admission into the higher vocational education system during the period 1992-2024, as well as on explanatory indicators related to the period 1989-2018. To determine which variables are most correlated with student enrollment in private higher vocational institutions, grey relational analysis is used and based on this, a BP neural network predictive model is built.

The enrollment rates of higher vocational colleges are estimated as the ratio of the number of students to that of the respective age group based on statistics information published by the National Bureau of Statistics.

2.2 Gray model construction

2.2.1 Gray correlation model

The grey relational analysis uses the grey relational model to measure the extent of relationship among system variables and explore how interconnected factors can also be changing at the same time during the process of system development. The relational degree between two systems is considered high if they have very similar trends of relative change across their development. If the trends are significantly different, the association is considered weak.

(1) Finding the Comparison and Reference Series

Reference series refers to a series of benchmark values that are developed based on a certain evaluative purpose whereas comparison series contains the series of data sequences that are constructed using the factors behind the change of a system.

Assume the reference series:

$$x_0 = \left\{ x_0(k) \middle| k = 1, 2, \cdots, n \right\} \tag{1}$$

Subsequence:

$$x_i = \left\{ x_i(k) \middle| k = 1, 2, \cdots, n \right\},\ i = 1, 2, \cdots, m \tag{2}$$

(2) Dimensionless Processing of Indicator System Data

The process of data preprocessing is done via normalization where the original data is rescaled to lie in a specific range. Such a method is often called min-max normalization:

$$r_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

where $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value. Since the highest and lowest values in a set of data are susceptible to change and outliers can easily skew them, this normalization technique tends to be most suitable in cases where the amount of data is moderate.

(3) Calculation of gray correlation coefficient

In the present paper, the overall enrollment level of private higher vocational schools is viewed as the reference series which is represented as:

$$x_0 = \left\{ x_0(1), x_0(2), \cdots, x_0(k), \cdots, x_0(n) \right\} \tag{4}$$

The indicator system related to each influencing factor becomes the object of assessment, which creates the comparison series, which is represented as:

$$x_i = \left\{ x_i(1), x_i(2), \cdots, x_i(k), \cdots, x_i(n) \right\},\ i = 1, 2, \cdots, t \tag{5}$$

The relation coefficient is calculated using the following formula:

$$\beta\left(x_i(k), x_0(k)\right) = \frac{\min\limits_i \min\limits_k \left|x_i(k) - x_0(k)\right| + \rho \max\limits_i \max\limits_k \left|x_i(k) - x_0(k)\right|}{\left|x_i(k) - x_0(k)\right| + \rho \max\limits_i \max\limits_k \left|x_i(k) - x_0(k)\right|} \tag{6}$$

where $\beta\left(x_i(k), x_0(k)\right)$ denotes the correlation coefficient between the samples of the comparison and reference series. ρ is the coefficient of discrimination, usually taking values between $\left[0,1\right]$. The differentiation is optimal when the value of ρ is 0.5.

(4) Calculate the degree of association

It is important to measure the level of correlation between the reference series and the comparison series because it will help define how each of the causal factors can be associated with the general educational level of private higher vocational institutions.

$$\pi_i = \frac{\sum_{k=1}^{n} \beta\left(x_i(k), x_0(k)\right)}{n} \tag{7}$$

where π_i denotes the extent of association between the ith comparison sequence and the reference sequence.

2.2.2 The GM(1,1) model

Grey prediction modelling is a statistical forecasting approach that maintains strong predictive performance even when available data are limited or incomplete, making it particularly well suited to small-sample problems. The theoretical foundation of this method lies in grey system theory, a branch of control theory originally developed to handle situations where information is partial or uncertain. Over the decades, it has been widely adopted across a broad range of disciplines, including meteorology, ecology, economics, biology, transportation, and process control, and both the theoretical underpinnings and practical applications of the field have advanced considerably. The influence of grey system theory has also given rise to a number of interdisciplinary research directions, among them grey control theory and the grey analysis of regional economies. A fundamental requirement of grey prediction is that the raw data must be arranged at equal time intervals. To reduce the inherent randomness present in the original time-series data, an accumulation process is applied to generate a new sequence, from which differential equations governing the reproduced series can subsequently be derived.

(1) Generate a new sequence

If the sequence is known to be:

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right\} \tag{8}$$

Then the cumulative generated columns are:

$$X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \cdots, x^{(1)}(n)\right\} \tag{9}$$

where $x^{(1)}(1) = x^{(0)}(1)$, $x^{(1)}(2) = x^{(1)}(1) + x^{(0)}(2)$, ..., $x^{(1)}(n) = x^{(1)}(n-1) + x^{(0)}(n)$, and call $X^{(1)}$ a cumulative sequence of $X^{(0)}$, denoted 1-AGO. combining the original sequences and subtracting the front and back neighboring data to obtain the corresponding cumulative generated series.

(2) Generate the mean sequence

Take the adjacent data of $X^{(0)}$ to generate the mean series, notated as:

$$z^{(0)}=\left(z^{(0)}(2),z^{(0)}(3),\cdots,z^{(0)}(n)\right) \tag{10}$$

$$z^{(0)}(k)=\alpha x^{(0)}(k)+(1-\alpha)x^{(0)}(k-1),\ k=2,3,\cdots,n \tag{11}$$

where $0\le\alpha\le1$, usually taken as $\alpha=0.5$.

The $GM\left(1{,}1\right)$ model is commonly applied in forecasting contexts where data availability is limited. Unlike many conventional approaches, it imposes no strict distributional requirements on the input data, though its predictive reliability is generally stronger over short to medium term horizons. The procedure is carried out through the following steps:

Original series:

$$X^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\} \tag{12}$$

Accumulate to generate the series:

$$X^{(1)}=\left\{x^{(1)}(1),x^{(1)}(2),x^{(1)}(3),\cdots,x^{(1)}(n)\right\} \tag{13}$$

a. Construct the mean sequence:

$$z^{(1)}=\alpha x^{(1)}(k)+(1-\alpha)x^{(1)}(k-1),\ k=2,3,\cdots,n \tag{14}$$

Usually α is taken as 0.5.

b. Develop the gray differential equation:

$$x^{(0)}(k)+az^{(1)}(k)=b,\ k=2,3,\cdots,n \tag{15}$$

where a is the development coefficient and b is the gray role quantity. Put (15) in matrix form:

$$\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \cdots & \cdots\\ -z^{(1)}(n) & 1\end{bmatrix}\begin{pmatrix}a\\ b\end{pmatrix}=\begin{pmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \cdots\\ x^{(0)}(n)\end{pmatrix} \tag{16}$$

$$X\beta=Y \tag{17}$$

c. Corresponding $GM\left(1{,}1\right)$ whitened differential equations:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}(t)=b \tag{18}$$

d. Solve for (17) using the least squares method:

$$\hat{\beta} = (a,b)^T = (X^T X)^{-1} X^T Y \tag{19}$$

Solving yields the parameters a and b, which are substituted into the differential equation (16) to obtain a discrete solution of the $GM(1,1)$ model:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, k = 1,2,\cdots,n \tag{20}$$

e. Restore the original series:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \tag{21}$$

Substituting (20) into equation (21) gives:

$$\hat{x}^{(0)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak}\left(1-e^{a}\right), k = 1,2,\cdots,n \tag{22}$$

2.2.3 Screening of Indicators for Predicting Private Higher Education Attendance Rate

To enhance the analysis rigour and relevance of the indicator choice, this paper will track changes in the higher vocational college enrollment over time (1992-2024) in a systematic way and investigate the factors behind them using grey relational analysis. The findings of this analysis produce a list of variables that can be used to forecast the number of students enrolling in private higher vocational colleges between 2025 and 2035. As a process of calculating the grey relational degree between every influencing factor and the enrollment rate of private higher vocational colleges, the following steps are taken:

Step 1: The first step is to take the sequence of the enrollment rates of private higher vocational institutions as the initial reference sequence $y(1), y(2), \cdots, y(n)$, and then set up eight indicator sequences as the corresponding comparison sequences $x_i(1), x_i(2), \cdots, x_i(n)$.

Step 2: Normalize all original sequences to remove any distortion caused by the magnitude variations and make it possible to calculate further. It is done through the calculation of the average of the reference sequence, the average of each comparison sequence separately, and the division of each term in each sequence by its respective average. The newly obtained transformed reference sequence is marked as $Y = \{y(1)', y(2)', \cdots, y(n)'\}$ and the transformed comparison sequences are marked as $X_i = \{x_i(1)', x_i(2)', \cdots, x_i(n)'\}$.

Step 3: Find the largest absolute difference b and the smallest absolute difference a:

$$b = \max_i\left[\max_k\left(\left\|Y(k) - X_i(k)\right\|\right)\right] \tag{23}$$

$$a = \min_i\left[\min_k\left(\left\|Y(k) - X_i(k)\right\|\right)\right] \tag{24}$$

Step 4: Calculate the gray correlation coefficient ξ of each indicator series, where ρ is the discrimination coefficient, generally take $\rho = 0.5$:

$$\xi\left(Y, X_i(k)\right)=\frac{a+\rho b}{\left\|Y-X_i(k)\right\|+\rho b},\begin{cases} i=1,2,\cdots,m \\ k=1,2,\cdots,n \end{cases} \tag{25}$$

Step 5: Calculate the gray correlation r_i of each indicator series, i.e., the average value of gray correlation coefficient:

$$r_i=\frac{\sum_{k=1}^{n}\xi\left(Y, X_i(k)\right)}{n} \tag{26}$$

where $i=1,2,\cdots,m$ represents the category of impact indicators, there are 8 pre-selected indicators in this paper, so $m=8$. $k=1,2,\cdots,n$ represents the year of the series, this paper collects relevant data from 1992-2024, so $n=32$.

2.3 BP Model Fitting to Predict Private Higher Education Attendance Rate

BP neural network is a type of multilayer feedforward networks and it is trained through error backpropagation algorithm. As illustrated in Fig. 1, the network contains M input nodes, $x_1, x_2, \cdots, x_M$, L output nodes, $y_1, y_2, \cdots, y_L$, and q neurons in the hidden layer.

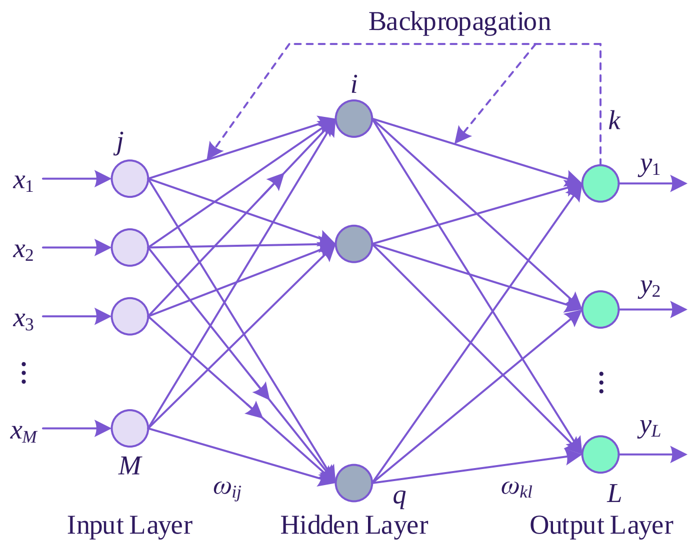


Figure 1: BP neural network structure

Suppose that N training samples are given and that example p is chosen to learn the network. In this case, the input net_i^p the output of the i th hidden-layer neuron associated with sample p may be expressed as:

$$net_i^p=\sum_{j=1}^{M}\omega_{ij}o_j^p-\theta_i=\sum_{j=1}^{M}\omega_{ij}x_j^p-\theta_i \tag{27}$$

where $i=1,2,\cdots,q$. q is the number of nodes in the implicit layer, and x_j^p and o_j^p are the inputs and outputs of input node j under the action of sample p, which are equivalent.

$j = 1, 2, \cdots, M$. ω_{ij} is the connection weight between input layer neuron j and hidden layer neuron i. θ_i is the threshold value of the hidden layer neuron i.

The output o_i^p of the i th neuron of the hidden layer is:

$$o_i^p = g\left(net_i^p\right) \tag{28}$$

where $g(\cdot)$ denotes the activation function.

The total input net_k^p of the k th neuron in the output layer is given by:

$$net_k^p = \sum_{i=1}^{q} \omega_{ki} o_i^p - \theta_k \tag{29}$$

where ω_{ki} is the connection weight between the output layer neuron k and the hidden layer neuron i, $k = 1, 2, \cdots, L$. θ_k is the threshold value of the output layer neuron k.

The actual output o_k^p is:

$$o_k^p = g\left(net_k^p\right) \tag{30}$$

The error function J_p is:

$$J_p = \frac{1}{2} \sum_{k=1}^{L} \left(t_k^p - o_k^p\right)^2 \tag{31}$$

where t_k^p is the desired output.

The error signal δ_k^p of the output layer node is:

$$\delta_k^p = -\frac{\partial J_p}{\partial net_k^p} = \left(t_k^p - o_k^p\right) o_k^p \left(1 - o_k^p\right) \tag{32}$$

The error signal δ_i^p of the hidden layer node is:

$$\delta_i^p = -\frac{\partial J_p}{\partial net_i^p} = -\frac{\partial J_p}{\partial o_i^p} \cdot o_i^p \left(1 - o_i^p\right) \tag{33}$$

The weighting coefficient $\Delta\omega_{ki}$ of any k th neuron of the output layer is corrected by the formula:

$$\Delta\omega_{ki} = \eta \delta_k^p o_i^p = \eta o_k^p \left(1 - o_k^p\right)\left(t_k^p - o_k^p\right) o_i^p \tag{34}$$

The incremental formula is:

$$\Delta\omega_{ki}\left(k+1\right) = \omega_{ki}\left(k\right) + \eta \delta_k^p o_i^p \tag{35}$$

where η is the learning rate and $\eta > 0$.

The weighting coefficient correction formula for any i th neuron of the hidden layer is:

$$\Delta\omega_{ij} = \eta\delta_i^p o_j^p = \eta o_i^p \left(1 - o_i^p\right)\left(\sum_{k=1}^{L}\delta_k^p \cdot \omega_{ki}\right)o_j^p \tag{36}$$

where o_j^p is the output of the j th neuron in the input layer.

The incremental formula is:

$$\Delta\omega_{ij}(k+1) = \omega_{ij}(k) + \eta\delta_i^p o_j^p \tag{37}$$

Based on the working principles of the BP neural network and the particular goals of this research, a BP network architecture is built to predict the enrollment rate of the private higher vocational institution. Each step of the process, including model creation, training, testing, and prediction, is done in MATLAB. A traditional neural network is usually a combination of three components, which include input layer, one or more hidden layers and an output layer. The input and output layers are located at both end of the network in the current model, whereas the number of hidden layers is determined by the design practicality. Based on these considerations, one hidden layer topology is accepted.

2.4 Gray BP Neural Network Combined Prediction Model

The GM-BP combined forecasting model utilizes the ability of the neural network as a universal function approximator. Once the GM(1,1) model has produced the residual series, the hybrid technique will determine the mapping relationship in that residual series and then use this to adjust and improve the initial GM(1,1) prediction values. Structural arrangement of the GM-BP model is shown in Figure 2.

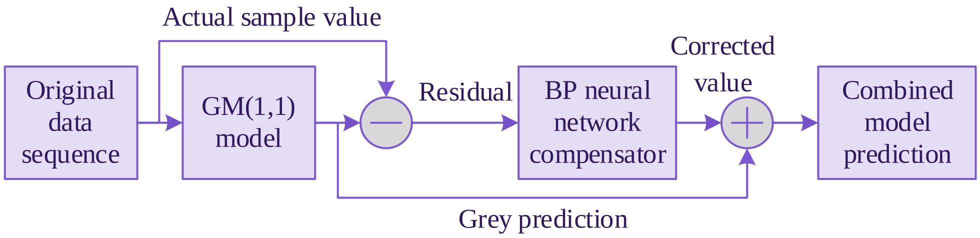


Figure 2: GM-BP structure

The steps for modeling the combined prediction model are as follows:

① Input the original data sequence $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right)$.

② Build the $GM(1,1)$ model to obtain the predicted data sequence $\hat{X}^{(0)} = \left(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n)\right)$, and build the sequence of residual data $E = X^{(0)} - \hat{X}^{(0)} = \left(e_1(1), e_1(2), \cdots, e_1(n)\right)$.

③ Establish a neural network model of residual sequence E, determine the prediction order as S, take the information of $e_1^{(0)}(i-1), e_1^{(0)}(i-2), \cdots, e_1^{(0)}(i-S)$ as the input samples for the training of the BP network, and the value of $e_1^{(0)}(i)$ as the value of the BP network training predictive expectation value, through the network training weights, thresholds, to get the residual sequence of the BP network prediction model.

④ Determine the prediction value of the gray neural network combination model of the residual sequence $\hat{X}^{(0)}(i,1)=\hat{X}^{(0)}(i)+\hat{e}_1^{(0)}(i)$.

3 Examples of forecasts of development trends in private higher vocational colleges and universities

3.1 Gray correlation analysis

3.1.1 Factors affecting the development of the scale of private higher vocational education

The growth of private higher vocational education is determined by a large variety of interrelated factors. Based on the existing situation, the available scholarly literature and the results of previous research, this paper has established four main categories and eight sub indicators as the key variables to be used in examining the determinants behind the process of developing higher vocational education. All these variables, which can be said to reflect the factors determining the scale of private higher vocational education, are shown in the table below. The eight indicators include: A1, higher vocational education expenditure (10,000 yuan); A2, mean expenditure on education per student in higher vocational education (100 million yuan); B1, GDP (100 million yuan); B2, consumer spending (yuan); B3, total retail sales of consumer goods (100 million yuan); C1, rate of unemployment in the urban areas (percent); C2, total population (10,000 persons); D1, number of secondary school graduates (10,000 persons).

Table 1: Influence factors of education scale of private vocational vocational colleges

Primary indicator		Secondary indicator	
A	Education input	A1	Higher vocational education funding (10,000)
		A2	Education education finance (100 million yuan)
B	Social and economic development	B1	GDP ($100 million)
		B2	Household consumption level (yuan)
		B3	Total retail retail (million yuan)
C	General social condition	C1	Urban unemployment (%)
		C2	Total population (10,000 people)
D	Source status	D1	High school graduates (10,000)

3.1.2 Gray correlation analysis of influencing factors

To minimize the distorting effects of inconsistent data units on computation and subsequent analysis, all raw data are converted into dimensionless values by dividing each observation by its corresponding mean. The processed data are displayed in Figure 3, where Z denotes the total number of students enrolled in private higher vocational institutions (10,000 persons).

To illustrate with a concrete example, Z, representing enrollment in higher vocational education, stands at 11,500,000 students; A1, expenditure on higher vocational education, amounts to 14,300,000 yuan; A2, the average per-student spending in higher vocational education, is 147,000,000 yuan; B1, GDP, reaches 164,000,000 yuan; B2, the resident consumption level, is recorded at 1,570 yuan; B3, total retail sales of consumer goods, amounts to 172,000,000 yuan; C1, the urban unemployment rate, sits at 0.99 percent; C2, the total population, is 10,800 persons; and D1, the number of secondary school graduates, is 0.99

million.

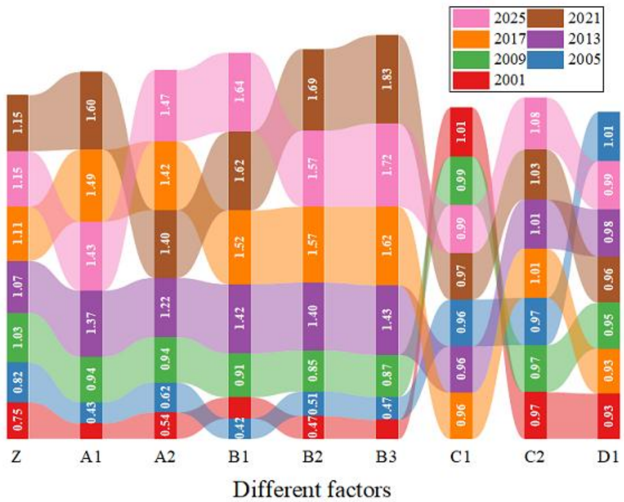


Figure 3: Partial data after non-quantitative processing

Heat map of correlations given in Figure 4 explains the relational strength between private higher vocational enrollment and any of the eight secondary indicators based on grey relational analysis. Of all the variables analyzed, enrollment is most strongly correlated with A2, i.e., per capita spending on higher vocational education at 0.8369. The next two are resident consumption level and GDP with coefficients of 0.7756. On the other hand, the quantity of graduates of secondary schools demonstrates a relatively weak correlation with higher vocational enrollment.

Figure 4: The correlation heat map of the number of students and the secondary index

3.2 Forecast of Development Trend of Private Higher Vocational Colleges and Universities

3.2.1 Enrollment Scale Projections

The projection of the enrollment trend of private higher vocational schools between 2025 and 2035 is depicted in Figure 5 based on the GM-BP model. The results show that the number of students enrolled in these institutions will be 934,796 in 2025 and increase slowly to reach 946,062 in 2035.

The GM-BP projections predict that the number of students who will be enrolled in private vocational colleges will peak at 976,377 students in 2027. In 2033, the predicted value is 970,001 which is 45,385 higher than the predicted value in 2032.

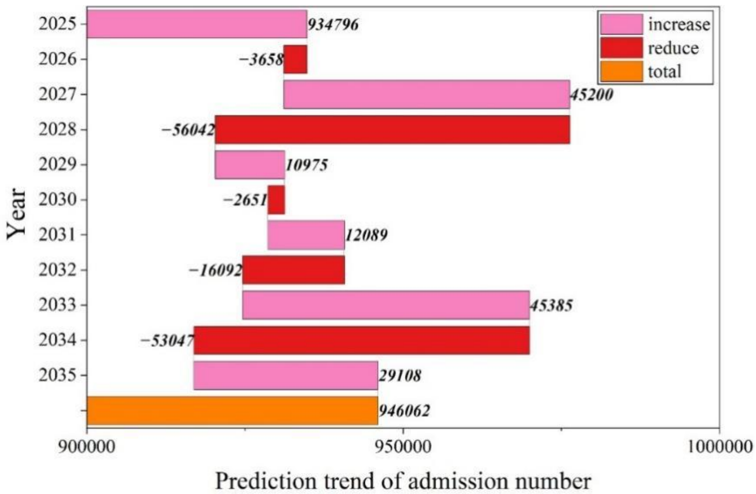


Figure 5: The prediction of the number of people in the private higher vocational higher

3.2.2 Size of the school population

The application of the GM-BP model is used to estimate the total enrollment in private higher vocational education between 2025 and 2035, and the estimates obtained are depicted in Figure 6. The figure indicates that there will be an upward trend in enrollment starting in 2025 and ending in 2027, after which enrollment will decrease up to 2030.

The smallest enrollment number throughout the whole projection period is observed in 2034, i.e. 2,823,792 students. The estimate of 2035 exceeds this bottom with 19,405 to make the projected number in 2035 reach a total of 2,843,198 students in private higher vocational institutions as of the end of the forecast horizon.

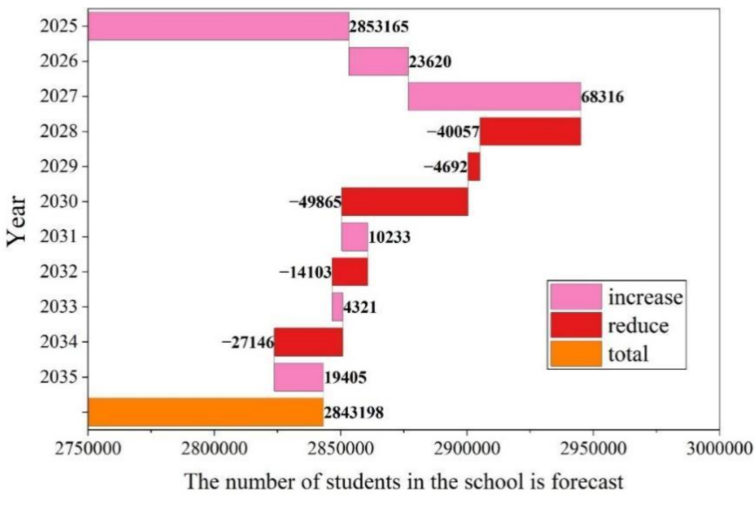


Figure 6: 2025-2035 higher vocational education prediction results

3.3 Forecast of Private Higher Education Enrollment Trends

3.3.1 Projected results

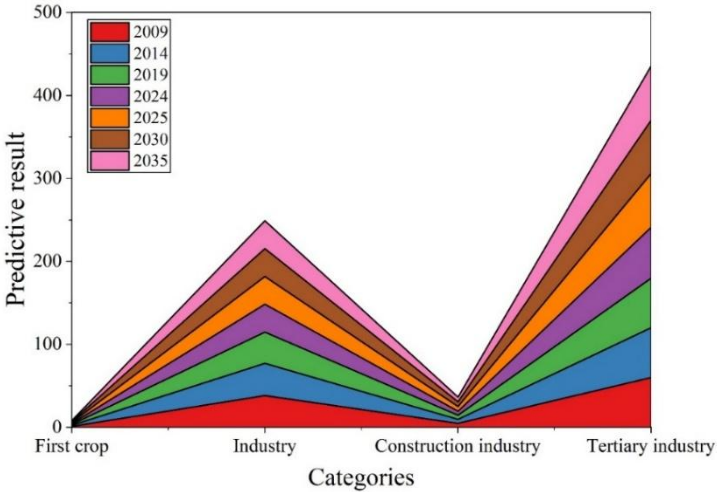
The prospect of predicting the future growth of privately owned higher vocational education has no theoretical or practical relevance except in the case where it is analyzed together with the industrial sectors that these programs belong to. It is then imperative to use trend prediction methods to predict, during the next decade, the movement of the primary sector, industry and construction, and the tertiary sector as a proportion of national GDP and the anticipated changes in the main categories of discipline most closely related to each.

Practically speaking, the proportional contributions of the primary sector, industry and construction, and the tertiary sector to national GDP, along with their closely related disciplinary categories, are supplied as input vectors to the DPS Data Processing System. It provides trend forecasts of the three-sector output composition as well as the enrollment composition of the highly correlated disciplinary categories. The analysis is based on information concerning the three-sector output composition and the corresponding disciplinary enrollment in 2009-2024 and projections of these trends until 2025-2035. Figures 7 shows the trend forecasts of enrollments in private higher vocational institutions during this period, with the results shown as panels (a) and (b), which show results by industrial sector and by disciplinary category respectively.

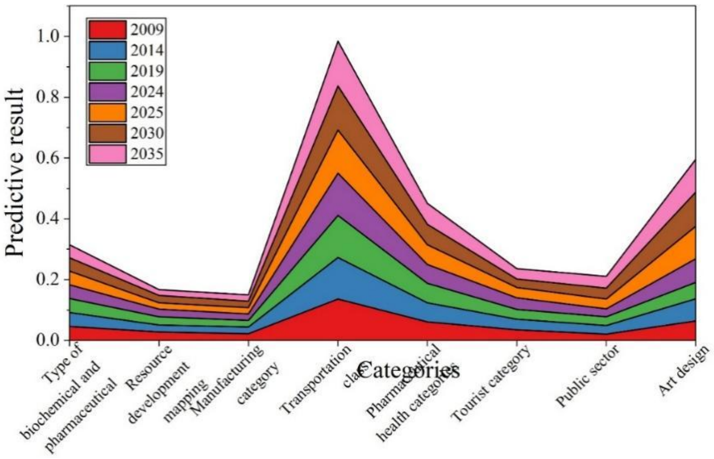
The GM-BP model produces 2035 projections of 1.15, 33.65, 5.72, and 65.32 in panel (a) representing primary sector, industry, construction, and tertiary sector respectively. The estimated transport enrollment share in 2035 is 0.147, which is higher than the respective 2030 value by 0.002.

Biochemical pharmaceutical and manufacturing sectors are projected to experience a slow decrease in their enrollment rates annually until it will stabilise. This trend indicates that the enrolment in these sectors has attained an average which is approximately synonymous with the existing level of economic progress and mirrors the existing structure of the demand on talents. It also shows that the rate of admissions in the higher vocational institutions remains responsive to market signals and industrial trends, so they can remain in line with the overall economic and market situation.

On the other hand, transportation and medicine and healthcare are expected to register consistent annual growth in enrollment share, which is a trend of the further development of the tertiary sector in the national economy.



(a) Different industries



(b) Different categories

Figure 7: The results of the enrollment trend of the private vocational colleges in 2035

3.3.2 Recommendations for specialization

Moreover, the tendencies of enrollment in agriculture, forestry, animal husbandry and fishery, water conservancy, materials and energy, textile and food, civil engineering, environmental protection, meteorology and safety, finance and economics, public security and law, culture and education, and electronics and information do not have a significant correlation with the development paths of their respective industries. In this regard, the data and the GM-BP model used in the present research cannot be seen as adequate to make reasonable comparison both among the trends within the disciplinary groupings considered and between these trends and the ones concerning the industries related to them.

A possible reasoning is the fact that the program planning process in private higher vocational schools is still not well adjusted to the current industry structure. It seems that some programs were set up with little regard to the productive orientation of the social industries or the specificity of the regional economic growth, which disconnect undermines the connection of the disciplinary offerings and the requirements of the industries. More data gathering is needed though so as not to allow conducting a more extensive research on the issues behind the program configuration.

The following recommendations are based on the enrollment trend projections, which were presented earlier in this paper and are aimed at the further growth of the private higher vocational education sector.

The development of programs in the private higher vocational institution should reactively respond to changes in the local industrial environment.

These projections made in the current research provide institutions with early warning about possible changes in the key disciplinary areas of private higher vocational education and thus allow them to plan programs better and basing them on empirical forecast evidence. It will enable schools to align their disciplinary frameworks with the local industry requirements much more quickly. Through tracking economic and educational tendencies and participating in predictive revision of program plans, private higher vocational institutions may put themselves in a stronger position to deal with industrial restructuring, technological modernization, and changing tendencies of economic growth and also use teaching resources more efficiently and without duplicating them unnecessarily.

(2) The structural consolidation of the program should be prioritized over its non-selective addition.

Currently, there are many higher vocational schools that provide very similar popularized programs, which causes obvious redundancy within this field. To follow popular specializations regardless of the strengths and peculiarities of educational institutions will hardly be beneficial to them in the long run. Such an unbridled proliferation of programs reduces the focus of the institution and undermines the integrity and quality of organized learning.

Accordingly, organizations are urged to pay closer attention to reorganizing the current programs. Programs that have proved to be oversupplied in the market and trend downwards in time series and time series matching of large categories need to be merged with similar programs or abolished entirely.

4 Conclusion

The current paper begins with describing some of the distinctive characteristics of the emerging stage of the private higher vocational institution development. The study subsequently uses grey relational analysis to identify the most relevant variables that could be used to predict enrollment of higher vocational institutions, and builds a BP neural network to predict the future size of such institutions, and incorporates it with the GM-BP approach to forecast their long-term development path.

These results indicate that the grey relational coefficients between higher vocational enrollment and three main indicators, which include average educational spending per student, GDP, and resident consumption, are 0.8369, 0.7756, and 0.7678 respectively. Amongst them, the average per-student spending has the highest correlation with enrollment, thus making it the most significant determinant of the increase in higher vocational education. According to the GM-BP forecast outcomes, there will be 2,843,198 students in the whole private higher vocational education system by 2035, and the number of students enrolling in private higher vocational colleges and universities will be 946,062. Considering the disciplinary structure, the share of biochemical pharmaceuticals and manufacturing is predicted to decrease slowly over time and retain relatively small shares, while transportation, medicine, and healthcare are forecast to maintain stable growth during the forecast period.

About the Author

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References

[1] Xue, E., & Li, J. (2022). Exploring the type-based vocational education system: Insights from China. Educational Philosophy and Theory, 54(10), 1670-1680.

[2] Chen, H., Li, Y., Zheng, E., Huang, Z., & Shi, K. (2021, April). Research and practice on the talent training model of advanced manufacturing line leaders in private higher vocational colleges——based on the perspective of modern apprenticeship. In 2021 2nd Asia-Pacific Conference on Image Processing, Electronics and Computers (pp. 127-131).

[3] Tadle, R. L., Valdez, L. P., Fernandez, R., Uy, C., & de Castro, B. (2021). Students' Experience of Service Quality of Technical Vocational Education and Training (TVET) Programs in Philiphines's Private Higher Educational Institutions (HEIs). Journal of

Technical Education and Training, 13(3), 29-39.

[4] Hu, J., Liu, H., Chen, Y., & Qin, J. (2018). Strategic planning and the stratification of Chinese higher education institutions. International Journal of Educational Development, 63, 36-43.

[5] Sun, G., Ding, Z., & Babaee, M. (2018). An Empirical Study on the Relationship between the Development of Vocational Education and the Upgrading of Industrial Structure in China. Rev. Cercet. Si Interv. Soc, 62, 40-55.

[6] Jiang, H. (2023). On the Relationship between Vocational Education and the Development of Digital Economy. International Journal of New Developments in Education, 5(5), 12-16.

[7] McGrath, S., & Yamada, S. (2023). Skills for development and vocational education and training: Current and emergent trends. International Journal of Educational Development, 102, 102853.

[8] Jiang, X., Xu, J., & Xu, X. (2024). An overview of domestic and international applications of digital technology in teaching in vocational education: Systematic literature mapping. Education and Information Technologies, 29(13), 16867-16899.

[9] Xu, J., Jiang, T., Wei, M., & Qing, Z. (2024). The digital transformation of vocational education: Experience and reflections of Shenzhen Polytechnic University. Vocation, Technology & Education, 1(1).

[10] Gu, M. (2024). Empowering vocational education through digital technology: Innovating the teaching landscape. International Journal of New Developments in Education, 6(6), 131-136.

[11] Dobricki, M., Evi-Colombo, A., & Cattaneo, A. (2020). Situating Vocational Learning and Teaching Using Digital Technologies--A Mapping Review of Current Research Literature. International journal for research in vocational education and training, 7(3), 344-360.

[12] Lytvyn, A., Lytvyn, V., Rudenko, L., Pelekh, Y., Didenko, O., Muszkieta, R., & Żukow, W. (2020). Informatization of technical vocational schools: Theoretical foundations and practical approaches. Education and Information Technologies, 25(1), 583-609.

[13] Hernández-Blanco, A., Herrera-Flores, B., Tomás, D., & Navarro-Colorado, B. (2019). A systematic review of deep learning approaches to educational data mining. Complexity, 2019(1), 1306039.

[14] Andriyani, D. A., Prayitno, H. J., Minsih, M., Jamali, A., Damayanti, V. S., Dipsatara, T., & Pradana, F. G. (2025). Opportunities and challenges for the development of deep learning in vocational schools: drivers of learning innovation in the industrial era 4.0. Journal of Deep Learning, 95-108.