Practical Knowledge Level Characteristics and Innovative Practice Achievement Transformation Mechanism of Vocational College Students

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Abstract—Cultivating talents with innovation ability is both the goal of higher vocational colleges and their responsibility given by the era. Focusing on improving the practical knowledge level of students means that students should be exposed to nature, society and problems through practical activities, thus providing the maximum space for them to think, explore, discover and innovate. As for existing studies on cultivating innovative ability of students and improving their practical knowledge level, they mainly have focused on ability evaluation and analysis of influencing factors, and few of them has involved analysis of their practical knowledge level characteristics. Therefore, this paper studied the characteristics and transformation mechanism of their innovative practice achievements. A multi-level comprehensive evaluation system was constructed, which aimed to evaluate the practical knowledge level of those students. The input dimension of quantized data of indexes was reduced in accordance with the principal component analysis (PCA). Then the quantized data of the low-dimensional indexes were mined by hierarchical clustering, and different training subsets were generated to participate in the evaluation model training. Based on the idea of clustering-prediction-integration, Gated Recurrent Unit (GRU) model was used for nonlinear integration of the output results of two-way Long Short-Term Memory (LSTM) model, which further fit the nonlinear characteristics in the quantized data of all indexes. By introducing Bootstrap-Data Envelopment Analysis (DEA) method, the transformation rate of innovative practice achievements of the students was collected and calculated in order to obtain a small calculation error. Experimental results verified the effectiveness of the proposed calculation method of the model.

Keywords—practical knowledge level, vocational college students, transformation of innovative achievements

1 Introduction

Based on the development of students' intelligence, innovation ability is a comprehensive ability to find and solve new problems and innovate things [1–4]. Our society today need talents with innovation ability, because this ability is a necessary characteristic of talents in the information age [5–9]. Cultivating talents with innovation ability is both the goal of higher vocational colleges and their responsibility given by the era [10–15]. In the innovation and entrepreneurship education, the practical knowledge level of students is mainly reflected in their ability to solve the unsolved or urgent problems in real life by using their professional knowledge and innovation skills and experience [16–22]. Focusing on improving the practical knowledge level of students means that the students should be exposed to nature, society and problems through practical activities, thus providing the maximum space for them to think, explore, discover and innovate. It is a very important subject to cultivate the innovation ability of students and improve their practical knowledge level in higher vocational education.

The starting point of Sang [23] was evaluating the entrepreneurship and innovation ability of vocational college students. Combined with the existing index system research and scientific practice, the author introduced the comprehensive evaluation method, constructed a three-level evaluation model with 40 specific indexes, and briefly analyzed the indexes. Practical innovation ability is the core content of talent training in higher education, which is directly related to the implementation of the strategy of strengthening China through human resource development. Starting from the practical demand and talent development law, Huang et al. [24] expounded the contents and necessity of the practical innovation ability of top-notch talents, and discussed the collaborative education mechanism of practical innovation ability in universities with industry characteristics. Finally, some thoughts were put forward on how to cultivate the practical innovation ability of top-notch talents in colleges with industry characteristics. The existing evaluation methods and indexes are not specific and the index weights are subjective. Zhang et al. [25] evaluated the practical innovation ability of graduate and undergraduate students by selecting evaluation indexes, and proposed an evaluation algorithm based on Deep Belief Network (DBN) and an improved algorithm based on the practical innovation ability model of graduate students. The experimental results showed that the improved algorithm had wider application scope and higher accuracy rate and overcame the problem of strong subjectivity of index weights, which is conducive to promoting the reform of talent training and the overall improvement of talent training quality. The current direction of talent training reform in colleges is to cultivate innovative talents in the field of Artificial Intelligence (AI), by integrating the concept of innovation and entrepreneurship education into the AI talent training plan, thus meeting the needs of society and industries. Jiao et al. [26] discussed in detail the cultivation of practical ability of AI talents in terms of developing innovation practice projects by establishing open source thinking, improving the innovation and entrepreneurship ability of undergraduate students based on discipline competition, designing multidisciplinary practice teaching models, constructing multidisciplinary innovative practice teaching models and soon. Then the authors built innovation and entrepreneurship practice platforms in order to meet the industry needs.

As for existing studies on cultivating innovation ability of students and improving their practical knowledge level, they mainly have focused on ability evaluation and analysis of influencing factors, and few of them has involved analysis of the characteristics of their practical knowledge level. However, in many cases, it is difficult to accurately evaluate the practical knowledge level of students. Due to the complexity and long duration of the innovation and achievement transformation, it takes a long time to verify the application value and feasibility of the innovation achievements. This leads to the questioning of the evaluation results using subjective evaluation methods, which is difficult to provide guidance for the ability improvement and development pf the students. Therefore, this paper studied the practical knowledge level characteristics and achievement transformation mechanism of the vocational college students. In Chapter 2, the paper constructed a multi-level comprehensive evaluation system for their practical knowledge level and reduced the input dimension of the quantized data of indexes using the PCA. Then the low-dimensional quantized data of indexes were mined by hierarchical clustering. The strongly related quantized data of indexes were divided into one category in order to generate different training subsets for participation in the evaluation model training. In Chapter 3, based on the idea of clustering-prediction-integration, GRU model was used for nonlinear integration of the output results of two-way LSTM model, which further fit the nonlinear characteristics in the quantized data of all indexes and improved the evaluation and feature prediction ability of the practical knowledge level. By introducing Bootstrap-DEA method, Chapter 4 collected and calculated the transformation rate of innovative practice achievements of the students in order to obtain a small calculation error. Experimental results verified the effectiveness of the proposed calculation method of the model.

2 Analysis of the practical knowledge level characteristics

The practical knowledge level of vocational college students is affected by three factors, namely, practical quality, practical skills and practical environment. Practice quality is embodied in three aspects, namely, practice motivation, practice spirit and practice thinking. The formation of practical skills requires the knowledge structure conditions and the practical activities conditions. The former includes basic knowledge, professional knowledge, instrumental knowledge or methodological knowledge, and comprehensive knowledge, and the latter includes cognitive practice, scientific experiment, production practice and social practice. In addition, practical skills are reflected in two aspects, that is, the ability of knowledge application, improvement and reconstruction, and the ability of studying and inventing technology, process and products. The practical environment is divided into three aspects, namely, system and mechanism of encouraging the practical innovation activities, the soft environment (cultural and teaching environment), and the hard environment (the scientific research and experimental training places inside colleges, and the practice bases outside). A multi-level comprehensive evaluation system for the practical knowledge level of the students can be constructed based on the above-said factors.

In this paper, features of the quantized data of each index were extracted periodically. The extraction process is shown in Figure 1. Firstly, the input dimension of the quantized data of indexes was reduced based on the PCA. Secondly, the hierarchical clustering mining of the quantized data of low-dimensional indexes was carried out. Thirdly, this paper rearranged the main characteristics of the exogenous variables of the quantized data of low-dimensional indexes, which divided the strongly related quantized data of indexes into one category. The quantized data in each category will participate in the evaluation model training as different training subsets.

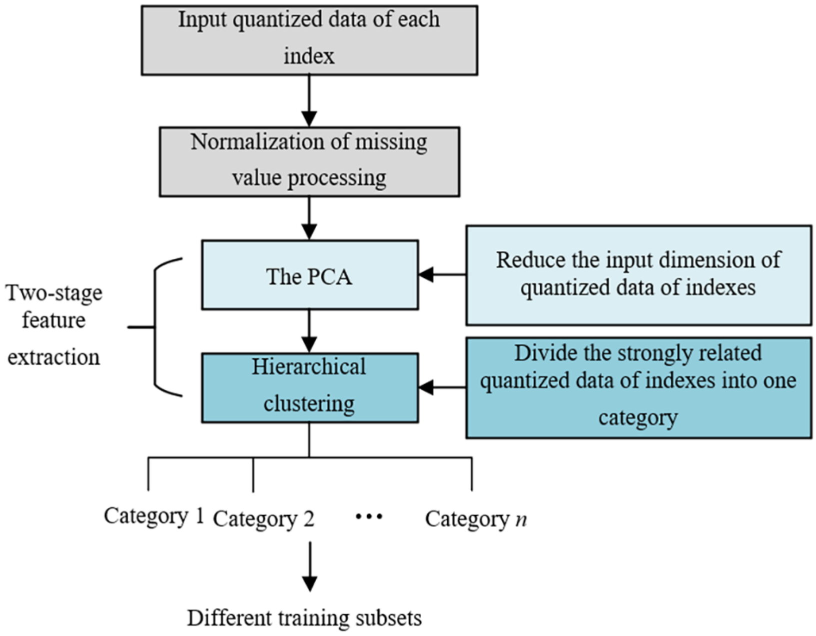


Fig. 1. Periodical feature extraction process

The basic steps of the PCA were detailed as follows:

Step 1: Set the input variables, composed of t indexes, and represented them with $A = (a_1, a_2, \ldots, a_t)$. The number of samples was represented by m. The following formula gave the original matrix expression:

$$A = (a_1, a_2, \ldots, a_t) = \begin{bmatrix} a_{11} & \cdots & a_{1t} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mt} \end{bmatrix} \tag{1}$$

Step 2: Assuming that the correlation coefficient of the original variables a_i and a_j was represented by $s_{ij}(i, j = 1, 2, \ldots, t)$, the following gave the calculation formula of the correlation coefficient matrix:

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1t} \\ s_{21} & s_{22} & \cdots & s_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ s_{t1} & s_{t2} & \cdots & s_{mt} \end{bmatrix} \tag{2}$$

s_{ij} was calculated by the following formula:

$$s_{ij} = \sum_{r=1}^{m} (a_{ri} - \bar{a}_i)(a_{rj} - \bar{a}_j) / \sqrt{\sum_{r=1}^{m} (a_{ri} - \bar{a}_i)^2 \sum_{r=1}^{m} (a_{rj} - \bar{a}_j)^2} \tag{3}$$

Step 3: Solved eigenvalue and eigenvector of the characteristic equation $|\mu I_t - T| = 0$. When t eigenvalues μ_i ($i = 1, 2, \ldots, t$) obtained were sorted in descending order, then $\mu_1 \geq \mu_2 \geq \ldots \geq \mu_t \geq 0$. The eigenvector obtained was expressed by o_i($i = 1, 2, \ldots, t$).

Step 4: Calculated the principal component contribution rate $\mu_i / \sum_{s=1}^{m} \mu_r (i = 1, 2, \ldots, t)$ and the cumulative contribution rate $\sum_{r=1}^{i} \lambda_r / \sum_{r=1}^{t} \mu_r (r = 1, 2, \ldots, t)$. In this paper, $\sum_{r=1}^{i} \lambda_r / \sum_{r=1}^{t} \mu_r$ should reach more than 85 percent, which was required in the characteristic analysis of practical knowledge level of vocational college students. At this time, the 1st, the 2nd … the n-th principal component corresponded with eigenvalue $\mu_1, \mu_2, \ldots, \mu_n$ ($n \leq t$).

Step 5: Calculated the principal component load, and performed the weighted sum of n principal components based on the variance contribution rate. The obtained results were outputted calculated scores of the quantized data samples of each index.

In hierarchical clustering, the distance between two sample points was represented by Euclidean distance. Assuming that two sample points A and B were represented by $A = (A_1, A_2, A_3, \ldots, A_m)$ and $B = (B_1, B_2, B_3, \ldots, B_m)$, and their distance was represented by $SQ(A, B)$, then the calculation formula was:

$$SQ(A,B) = \sqrt{(A_1 - B_1)^2 + (A_2 - B_2)^2 + \cdots + (A_m - B_m)^2} \tag{4}$$

In hierarchical clustering, equivalence of the distance between two clustering categories was performed through minimum (single chain) distance, maximum (full chain) distance and average (group average) distance. Assuming that two sample points were represented by t_i and t_j, and the two clustering categories were represented by d_i and d_j, which satisfied $t_i \in d_i$ and $t_j \in d_j$, the following gave the calculation formula of the closest distance of all sample points in two clustering categories, i.e. the minimum (single chain) distance:

$$c_{\min}(d_i, d_j) = \min \left\| t_i - t_j \right\| \tag{5}$$

The following gave the calculation formula of the longest distance of all sample points in two clustering categories, i.e. the maximum (full chain) distance:

$$c_{\max}(d_i, d_j) = \max \left\| t_i - t_j \right\| \tag{6}$$

Assuming that the numbers of samples of clustering categories d_i and d_j were represented by m_i and m_j respectively, the following formula gave the average distance of all sample points in the two clustering categories, i.e. the average (group average) distance:

$$c_{avg}(d_i, d_j) = \frac{1}{m_i m_j} \sum \sum \left\| t_i - t_j \right\| \tag{7}$$

3 Evaluation of practical knowledge level of vocational college students

According to clustering-prediction-integration, this paper used the GRU model for nonlinear integration of the output results of two-way LSTM model, which further fit the nonlinear characteristics in the quantized data of all indexes and improved the evaluation and feature prediction ability of practical knowledge level of vocational college students. This model combined feature extraction with deep learning model, which made up for the shortcomings of traditional evaluation strategy and single neural network model in terms of feature extraction and evaluation performance. Figure 2 shows the evaluation process of practical knowledge level. Figure 3 shows the bidirectional LSTM model architecture.

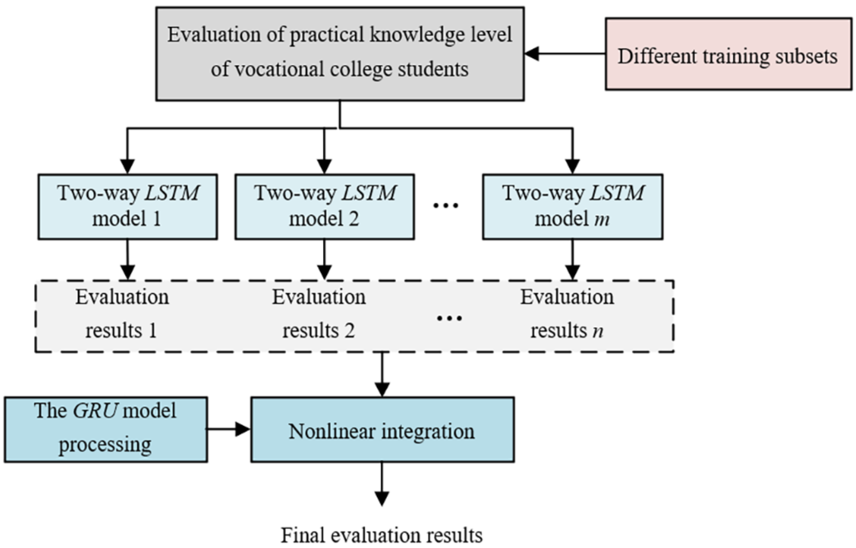


Fig. 2. Evaluation process of practical knowledge level

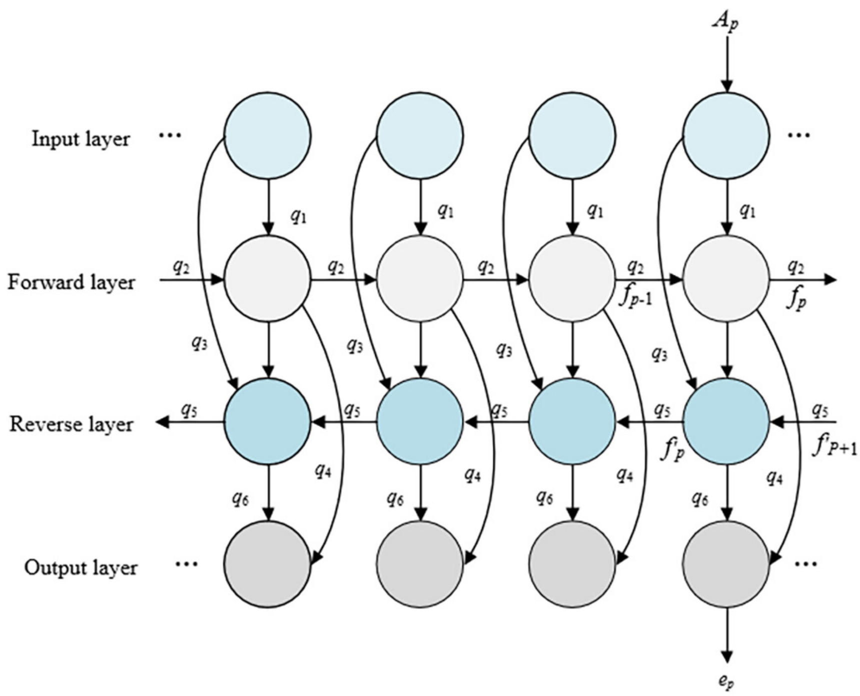


Fig. 3. Two-way LSTM model architecture

It was assumed that ε represented the *sigmoid* activation function, a_p represented the current input vector, f_p represented the current hidden layer vector, and y_g, Q_g and V_g represented the bias input weight and the cycle weight of the forget gate, respectively. In the bidirectional LSTM neural network model, the following gave the expression of forget gate g_p, which determined what information should be removed from the cells:

$$g_p = \varepsilon(y_g + Q_g a_p + V_g f_{p-1}) \tag{8}$$

The expression of external input gate h_p was:

$$h_p = \varepsilon(y_h + Q_h a_p + V_h f_{p-1}) \tag{9}$$

Cell state D_p, updated based on D_{p-1}, was obtained by the following formula:

$$D_p = g_p D_{p-1} + h_p \tanh(y_d + Q_d a_p + V_d f_{p-1}) \tag{10}$$

Finally, the information output under the control of input gate was $f_p = e^*_p tank(D_p)$, where $e_p = e(y_o + Q_e a_p + V_e f_{p-1})$.

The bidirectional LSTM model was composed of two LSTM neural networks, which went through forward training and reverse training. The following gave the main formula:

$$f_p = g(q_1 A_t + q_2 f_{p-1}) \tag{11}$$

$$f'_p = g(q_3 A_t + q_5 f'_{p-1}) \tag{12}$$

$$e_p = h(q_4 f_p + q_6 f'_p) \tag{13}$$

where, A_p represents the input at time p, the corresponding weight matrix is represented by q_1, q_2, q_3, q_4, q_5 and q_6, f_{p-1} represents the output of the previous time, f_p represents the output of time p in the forward layer, f'_{p+1} represents the output of the next time, f'_p represents the output of time p in the reverse layer, and e_p represents the output of time p.

4 Calculation of transformation rate of innovative practice achievements of vocational college students

Figure 4 shows the transformation process of innovative practice achievements. As for students with certain practical motivation, practical spirit and practical thinking ability, their expectations of innovative practice results produced innovative practice behavior and practical results. The achievements were transformed after completing the verification of application value and reliability. In the transformation process, students improved their practical knowledge level and enhanced their innovative quality, thus forming a virtuous innovative practice cycle.

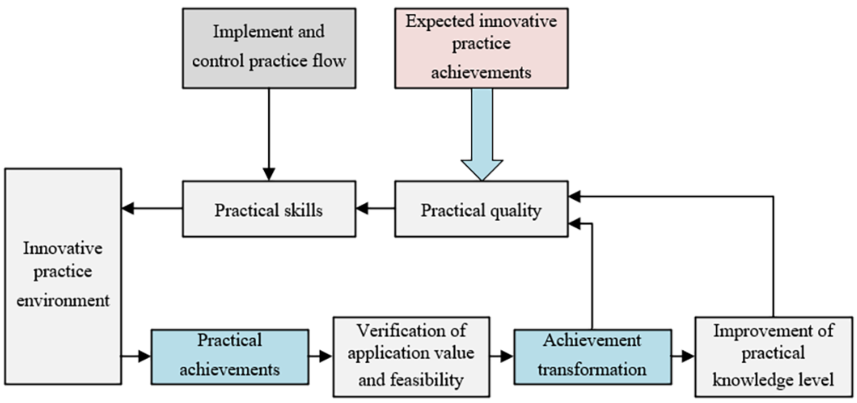


Fig. 4. Transformation process of innovative practice achievements

After sorting out and summarizing the existing literature, it is learned that a problem need to be further verified, i.e. whether the quantization mechanism research results of innovative practice transformation have universal applicability or not. The existing research on the transformation rate of innovation practice achievements is an important issue of concern to the theoretical and practical circles. Therefore, based on the field and network survey results and combined with the innovative practice knowledge level characteristics of regional vocational college students and innovative practice transformation characteristics, obtained in the previous section, this paper collected and calculated the achievement transformation rate of vocational college students by introducing the Bootstrap-DEA method in order to obtain a small calculation error.

In the traditional model using the DEA method, assuming that there were m decision-making units $DUM_j (j = 1, 2, \ldots, m)$, r different outputs $b_{sj} (s = 1, 2, \ldots, r)$ could be obtained by using n inputs a_{ij} $(i = 1, 2, \ldots, n)$. Assuming that v_s and u_i represented different weights of different inputs and outputs, then o_j, the efficiency value of DMU_j, was calculated by the following formula:

$$o_j = \sum_s v_s b_{sj} / \sum_i u_i a_{ij} \tag{14}$$

For any DMU_j, its corresponding weight could be obtained by solving its nonlinear programming problem. That is, when ρ represented a small positive number, the measured value of objective decision unit DMU_0 was obtained by solving the following formula:

$$\begin{aligned} & o_0 = \max \sum_s v_s b_{s0} / \sum_i u_i a_{i0} \\ & s.t. \sum_s v_s b_{sj} / \sum_i u_i a_{ij} \leq 1, \forall j \ vs, ui \geq \rho; \forall s, \forall i \end{aligned} \tag{15}$$

The above formula is the traditional CCR (A.Charnes, W.W.Cooper and E.Rhodes) model using the DEA method, where ω_0 is the technical efficiency value of DMU_0, μ_i is the weight, r_i is the input slack variable and $r + s$ is the output slack variable. By applying the fractional programming theory, the CCR model could be transformed into a linear programming problem as shown in the following formula:

$$\begin{aligned} & \min \omega_0 - \left(\sum_i r_i^- + \sum_r r_r^+ \right) \\ & s.t. \sum_j \mu_j a_{ij} + r_i = \omega_0 a_{i0}; i = 1, \ldots, n \\ & \sum_j \mu_j a_{ij} - r_i^+ = b_{s0}; s = 1, \ldots, r \ \mu_j, r_i^-, r_r^+ \geq 0; \forall i, j, s \end{aligned} \tag{16}$$

On the basis of the above formula, the convexity constraint related to μ_i was added, i.e. $\mu_i = 1$. The BCC (Banker, Charnes and Cooper) model, based on the assumption of Variable Return to Scale (VRS), as shown in the following formula could be constructed:

$$\begin{aligned} &\min \omega_0 - \rho\left(\sum_s r_r^+ + \sum_i r_i^-\right) \\ &s.t.\sum_j \mu_j a_{ij} + r_i = \omega_0 a_{i0}; i = 1,...,n \\ &\sum_j \mu_j b_{sj} + r_i^+ = b_{s0}; r = 1,...,r \\ &\sum_j \mu_j = 1 \; \mu_j, r_i^-, r_r^+ \geq 0; \forall i, j, s \end{aligned} \tag{17}$$

Because models CCR and BCC have not taken into full consideration the error factors, the Bootstrap-DEA method can solve this problem and has achieved good empirical results. Based on the original input-output sample set, transformed from innovation practice achievements collected, this paper used DEA method to calculate the efficiency value ω'_j of each decision unit DUM_j. Assuming that y represented the y-th repeated sampling using the Bootstrap method, then m samples ω_{1y}, ω_{2y} …, ω_{my} ($y = 1, 2, \ldots, Y$) were drawn from $\omega_1, \ldots \omega'_m$ by using the repeated sampling method. Finally, smoothing of samples $\omega^*_{1y}, \ldots \omega^*_{my}$ was performed. Assuming the smoothing parameter was represented by f, and the random error term was represented by ρ, the smoothing formula was:

$$\omega^*_{jy} = \overline{Y} + \frac{\overline{\omega}^*_{jy} - \overline{Y}}{(1 + f^2 / \varepsilon'^2_0)^{1/2}} \tag{18}$$

where,

$$\begin{aligned} &\overline{Y} = \frac{1}{m}\sum_{j=1} \omega_{jy} \\ &\overline{\omega}^*_{jb} = \begin{cases} \omega_{jy} + f\rho^*_j, if \quad \omega_{jy} + f\rho^*_j \geq 1 \\ 2 - \omega_{jy} - f\rho^*_j, if \quad \omega_{jy} + f\rho^*_j < 1 \end{cases} \quad \varepsilon'^2_0 = \frac{1}{m}\sum_{j=1}(\omega'_j - \overline{\omega'_j}) \end{aligned} \tag{19}$$

$a^*_{jy} = (\omega'_{jy} / \omega^*_{jy})a_j$ was obtained by using ratio $\omega'_{jy} / \omega^*_{jy}$ to adjust the original input data, transformed from innovative practice achievements. ω'_{jy}, efficiency value of the DEA, was obtained through calculation by using the adjusted input data a^*_{jy} and the original output data. ω'^*_{jy} $(y = 1, \ldots, Y)$ was obtained by repeating the previous steps for Y times.

The deviation $PC'(\omega'_j)$ was calculated based on formula $Y^{-1}\sum_{y=1}^{Y}\omega'^{*}_{jy} - \omega'_j$, and the corrected efficiency value was calculated based on formula $\omega''_j = \omega'_j - PC'(\omega'_j) = 2\omega'_j - Y^{-1}\sum_{y=1}^{Y}\omega'^{*}_{jy}$.

If the confidence level of the results was represented by x, then $Y\omega'^{*}_j - \omega'_j$ could be sorted in ascending order according to $ZS(-y_x \leq \omega'^{*}_{jy} - \omega'_j \leq -x_x) = 1-\phi$. After proposing the value of $100\phi/2\%$, the endpoint values at both ends were $-y'_\phi$和$-x'_\phi$. The confidence interval $\omega'_j - x'_\phi \leq \omega_j \leq \omega'_j + y'_\phi$ was obtained through the above steps.

5 Experimental results and analysis

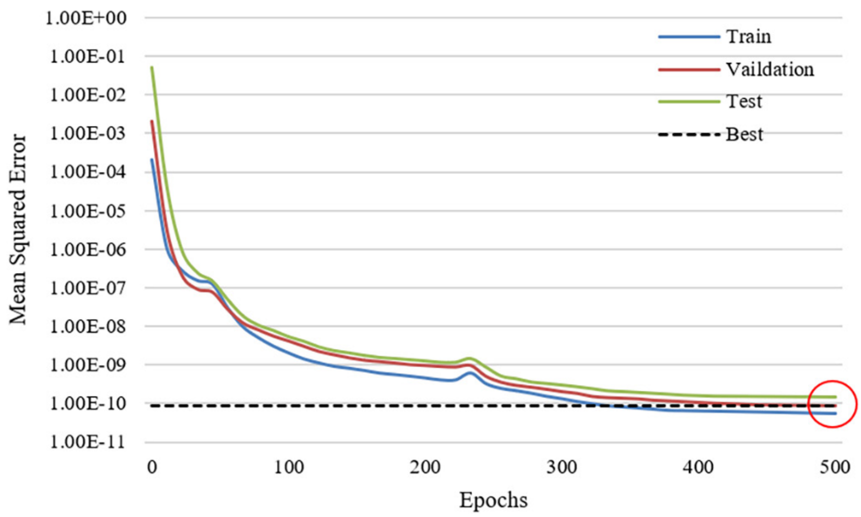
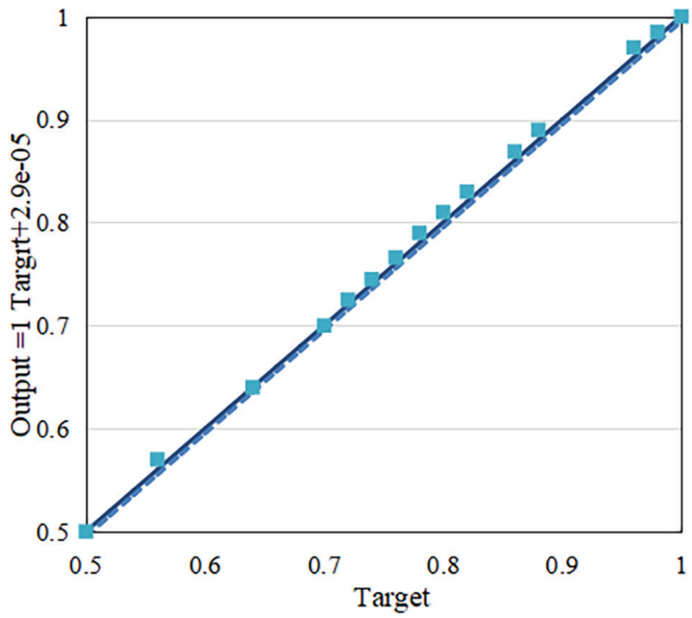
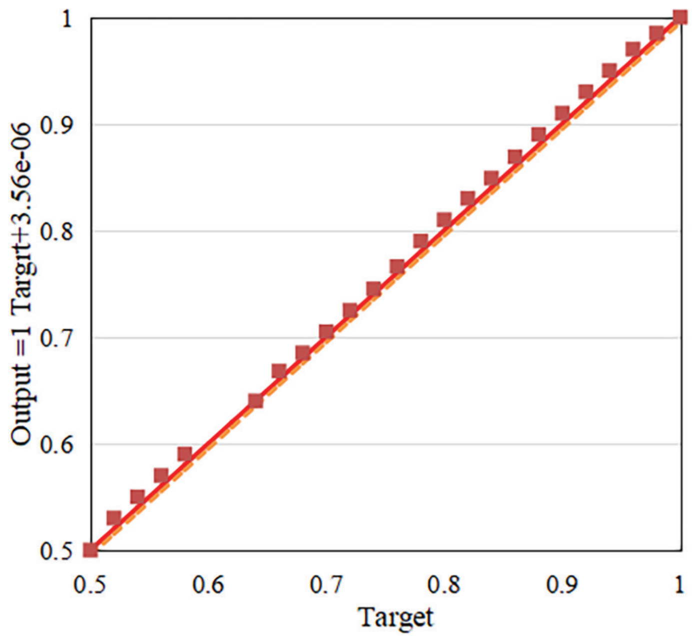


Fig. 5. Training results of evaluation model



(a)



(b)

Fig. 6. Data fitting results of evaluation model

Table 1. Statistical table of quantized data of indexes

Indexes	Minimum Value	Maximum Value	Mean Value	Standard Deviation
Practical motivation	79	95	86.32	4.53
Practical spirit	56	94	81.34	1.42
Practical thinking	70	86	77.86	5.96
Knowledge structure conditions	65	82	72.57	2.54
Practical activity conditions	52	87	62.23	7.53
Knowledge application ability	57	91	75.42	3.21
Research and invention ability	45	76	57.95	7.55
Soft environment for practice	60	77	68.24	8.92
Hard environment for practice	63	82	78.41	4.56

Figure 5 shows the training results of the practical knowledge level evaluation model for vocational college students. According to Figure 5, the model tends to be stable and the prediction accuracy basically meets the requirements after iterative training for about 400 times. Figure 6 shows the fitting effect of the evaluation model on the quantized data of indexes in training samples and test samples. It can be seen from the figure that the prediction accuracy of the constructed model is very high, which can be used for further calculation and simulation analysis of the transformation rate of innovation practice achievements.

The existing studies are more inclined to evaluate the practical knowledge level of vocational college students based on the cross-sectional data, which has insufficient robustness in the results. In order to solve this problem and reflect the changing trend of their practical knowledge level in the process of innovation and practice, this paper sorted out the original data of evaluation indexes of 9 sampled vocational colleges, i.e. the quantized data of 9 indexes, namely, practical motivation, practical spirit, practical thinking, knowledge structure conditions, practical activity conditions, knowledge application ability, research and innovation ability, soft environment and hard environment. In consideration of the time lag effect between the input of innovative practice activities of students and the output of their innovative achievements, this paper gave the statistical results of quantized data of indexes (Table 1) by referring to the existing treatment methods of periodical lag in the achievement transformation.

Table 2. Practical knowledge level improvement and achievement transformation efficiency of vocational college students

Vocational Colleges	2009–2011			2012–2014			2015–2017			2018–2020		
	1st Stage	2nd Stage	Whole	1st Stage	2nd Stage	Whole	1st Stage	2nd Stage	Whole	1st Stage	2nd Stage	Whole
1	1.000	1.000	1.000	1.000	0.602	0.995	1.000	0.563	1.000	0.998	0.752	1.000
2	1.000	0.675	0.834	0.926	0.382	0.836	1.000	0.371	0.972	1.000	0.270	0.975
3	1.000	0.172	1.000	1.000	0.458	0.936	1.000	0.394	0.950	1.000	0.132	0.953
4	1.000	0.124	0.586	0.974	0.973	0.535	1.000	0.102	0.656	1.000	0.125	0.732
5	1.000	0.118	0.571	1.000	1.000	0.624	1.000	0.051	0.532	1.000	0.057	0.675
6	1.000	0.169	0.573	0.802	0.811	0.580	1.000	0.164	0.640	0.958	0.119	0.607
7	0.706	0.065	0.482	0.831	0.056	0.421	0.872	0.048	0.554	1.000	0.162	0.695
8	0.758	0.104	0.512	0.736	0.112	0.534	0.842	0.143	0.608	1.000	0.094	0.667
9	0.352	0.095	0.493	0.481	0.053	0.397	0.693	0.059	0.509	0.627	0.060	0.581

Based on the maxDEA software, this paper collected and calculated the transformation rate of innovative practice achievements of those students by introducing the Bootstrap-DEA method. The results are shown in Table 2. In the first stage, the students improved their practical knowledge level. In the second stage, the practical innovation achievements were transformed. The whole represented the complete stage of the first stage plus the second stage.

According to the table, from the perspective of the practical knowledge level improvement stage, the improvement rate of students in sampled higher vocational colleges is as high as 0.711, and shows a steady upward trend. It shows that the sampled colleges pay attention to the practical education of students and give full play to the positive role of innovation and entrepreneurship education. From the perspective of the practical innovation transformation stage, the situation of the colleges is not optimistic, with transformation rate of 0.167 only. In addition, the transformation rate showed a downward trend year by year during 2012–2017. From the above results, it can be concluded that the sampled colleges attach importance to the innovative practice education of students; however, there is no sound achievement transformation mechanism and the benign operating mechanism for the transformation has not yet formed.

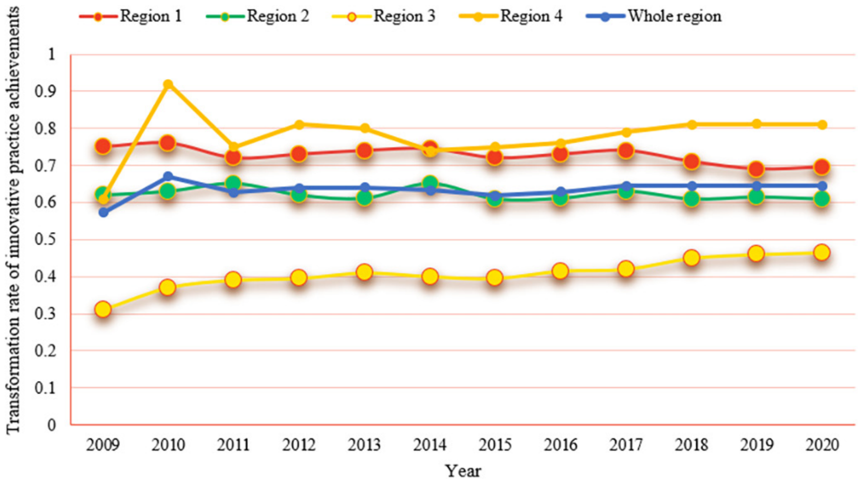


Fig. 7. Transformation rate of practical innovation achievements of students in regional vocational colleges

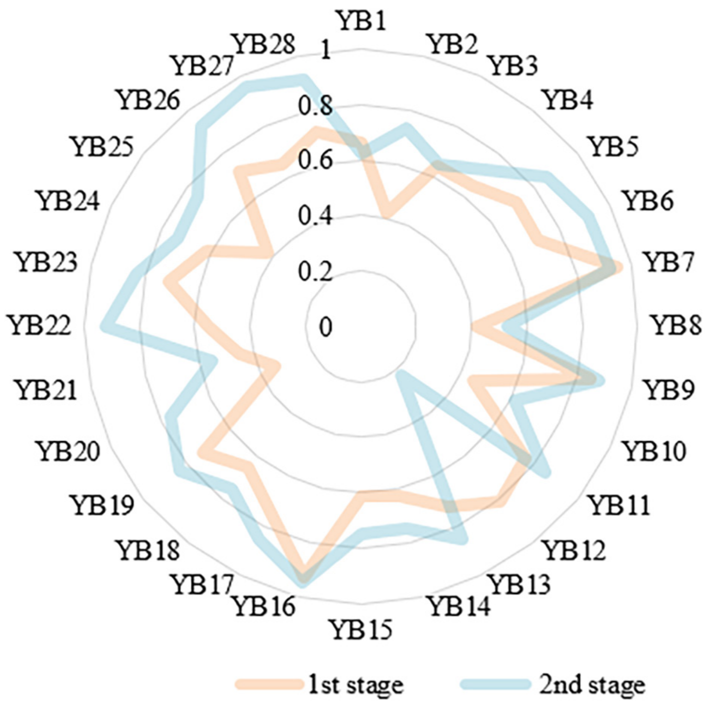


Fig. 8. Comparison of innovative practice achievement transformation rate of students at different stages

In this paper, 9 sampled colleges were divided into 4 regions in order to compare the innovation transformation rate among different regions. The comparison results are shown in Figure 7. According to the figure, there is a small gap in the transformation rate in the 4 regions and the whole region; the change trend of the transformation rate is relatively flat; relatively obvious distribution characteristics have not yet appeared. In addition, this paper compared the transformation rate at different stages, and the comparison results are shown in the radar chart in Figure 8. According to Figure 8, the transformation rate has significantly improved, with the number increasing more than 80%. It shows that the participation of innovative practice activities plays a positive role in promoting the achievement transformation; colleges with good innovation management ability provide high-quality resources to promote the innovative practice education, which is conducive to the improvement of the practical knowledge level and the realization of achievement transformation.

6 Conclusion

This paper studied the characteristics of practical knowledge level of vocational college students and transformation mechanism of their innovative practice achievements. After constructing the multi-level comprehensive evaluation system for their practical knowledge level, this paper used the PCA to reduce the input dimension of the quantized data of the indexes. Then the quantized data of the low-dimensional indexes were mined by hierarchical clustering, and different training subsets generated participated in the evaluation model training. With the idea of cluster-prediction-integration, the GRU model was used for nonlinear integration with the output results of two-way LSTM model, which further fit the nonlinear characteristics in the quantized data of each index. In addition, the Bootstrap-DEA method was introduced to collect and calculate the transformation rate of innovative practice achievements of the students, thus obtaining a small calculation error. The related calculation and analysis results were given in this paper. This paper represented the training results of the practical knowledge level evaluation model, which verified the effectiveness of the model. In addition, this paper sorted out the original data of the evaluation indexes of 9 sampled colleges, and gave the statistical results of the quantized data of the indexes. Finally, after comparing the achievement transformation rate in different regions and at different stages, the paper gave the corresponding analysis results.

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