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Expansion of Youth Entrepreneurial Opportunities and Employment Path Analysis under the Highly Skilled Personnel Training Model

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SUMMARY: *As the main force of high-skilled personnel, the development of entrepreneurial ability and the expansion of employment paths of young people are the key dimensions to measure the effectiveness of talent cultivation. This study conducted a questionnaire survey on 2,950 youths from six different types of high efficiency, and analyzed the structure, level and group differences of youth entrepreneurial ability by using factor analysis and improved K-means cluster analysis to effectively identify youth entrepreneurial opportunities and employment paths. The study found that youth entrepreneurial ability can be deconstructed into five main factors: entrepreneurial knowledge ability, individual personality traits, opportunity exploration ability, organizational management ability, and innovation and creativity ability, etc. The organizational management ability of the study participants performed best, while entrepreneurial knowledge ability performed weakest, with a mean of only 3.561. The youth group was clustered into three categories of strong, medium and weak entrepreneurial ability, with the proportion of 40.334%, 38.902%, and 20.9%, respectively. The youth group is clustered into three categories of strong, medium and weak entrepreneurial ability, with the proportions of 40.334%, 38.902% and 20.764% respectively, which is in the middle-upper level, but the internal development is uneven. Therefore, in order to effectively expand youth entrepreneurial opportunities and optimize employment paths, a cultivation system of classified guidance and whole process empowerment should be constructed to promote the deep integration of the education chain, talent chain and industrial chain, and to provide reliable solutions for youth to achieve higher-quality entrepreneurship and employment.*

KEYWORDS: *Entrepreneurship; Employment paths; Factor analysis; K-means clustering; Highly skilled individuals*

1 Introduction

In the context of sustained economic development, the market has a higher demand for skilled personnel, training more highly skilled personnel has become a hot issue at this stage. Whether for the enterprise or national development, highly skilled personnel is to realize technological innovation and the transformation of the results of the indispensable core force, in order to improve the quality of the economy at the same time, to cultivate a highly skilled, high-quality technical personnel team for the enterprise to realize the transformation of the equipment and technological innovation has a very important significance [1-4]. Social and economic

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development not only needs a large number of party and government, business management, special technology and other aspects of the talent, but also need to establish a structure of scientific, skilled, dedicated team of highly skilled personnel. In the labor market, the employment competitiveness of high-quality and high-skilled labor talents is stronger, and such talents are necessary to promote the good development of advanced productive forces, are the main prerequisite for economic growth and social development, and are the key measures to promote the long-term and stable development of social and economic development, and to enhance the competitive strength [5-9].

With the digital transformation of industries and the development of digital economy, industries are gradually upgraded, and the demand for labor in economic and social development is adjusted accordingly, giving rise to a large number of new industries and new types of jobs, and promoting structural changes in the job market [10-12]. And the application of high-tech, automation and information technology has improved the safety, comfort and workload in the workplace and improved the quality of employment [13]. These changes support the training of highly skilled personnel. And youth, as a key labor resource in the job market, need to have higher adaptability and high skills under technological development as a way to maintain high competitiveness in the job market and entrepreneurial market [14-16]. However, the contradiction between professional skills and jobs, and the contradiction between supply and demand in the market have become the main problems restricting youth employment and entrepreneurship [17, 18]. Based on this, it highlights the necessity of broadening youth entrepreneurship opportunities and optimizing their employment paths.

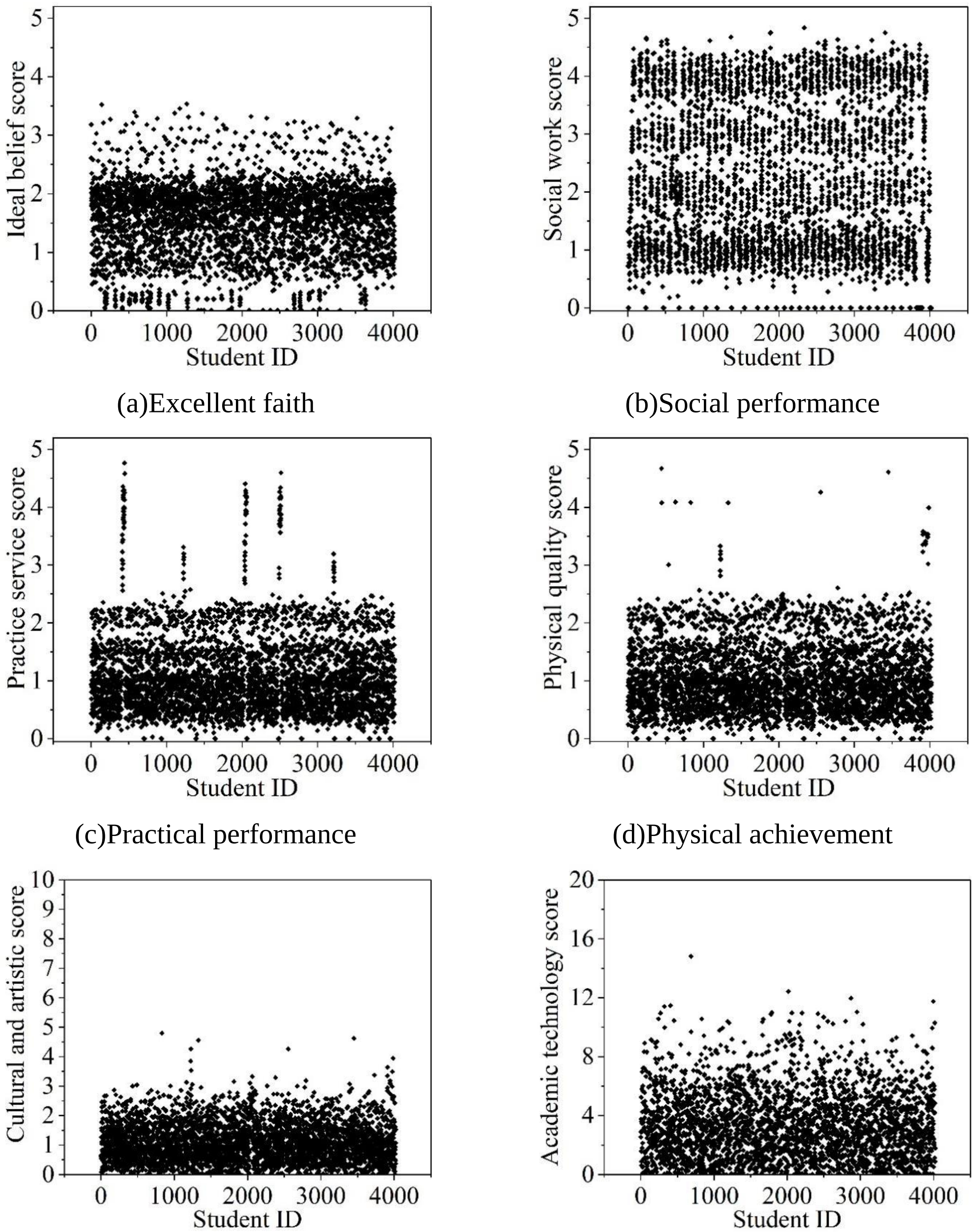
This study applies factor analysis and k-means cluster analysis method incorporating the coefficient of variation to identify the structural dimensions and group distinctions of youth entrepreneurship. Factor analysis was first utilized to extract a small number of public factors with explanatory power from multiple indicators, effectively reducing the dimensionality of the data and identifying the entrepreneurial competence components. The improved k-means cluster analysis method optimizes the attribute weight allocation through the introduced variable coefficient weight vector, reduces the interference of non-relevant features on the classification results, and enhances the identification of group differences in youth entrepreneurial competence. In order to comprehensively assess the current situation and differences of youth entrepreneurial ability, young students from six universities were selected as the research subjects, and a structured questionnaire survey was conducted on them.

2 Methods for identifying youth entrepreneurship in the high-skilled personnel training model

2.1 Data sources and pre-processing for youth in high schools

The data on college youth comes from the entrepreneurship and employment-related data of 4,020 undergraduate graduates from all faculties of six colleges and universities in western China, with the current college students as the main subjects of the survey. It records the basic personal information of the college students, the employment units of the college graduates, the location of the employment units of the graduates, the nature of the employment units of the graduates, as well as the GPA and ranking of the college students during the four years of schooling.

The scatter plot of the distribution of each achievement of students' classroom raw data under the cultivation mode of high-skilled talents is shown in Fig. 1, and Figs. (a) to (f) are the achievement of ideals and beliefs, the achievement of social work, the achievement of practical service, the achievement of physical education, the achievement of culture and art, and the achievement of academic science and technology, respectively. From the figure, it is obvious that there are more 0 values in the raw data, such data will have a certain impact on the clustering results, so it is necessary to carry out data preprocessing on the raw data.



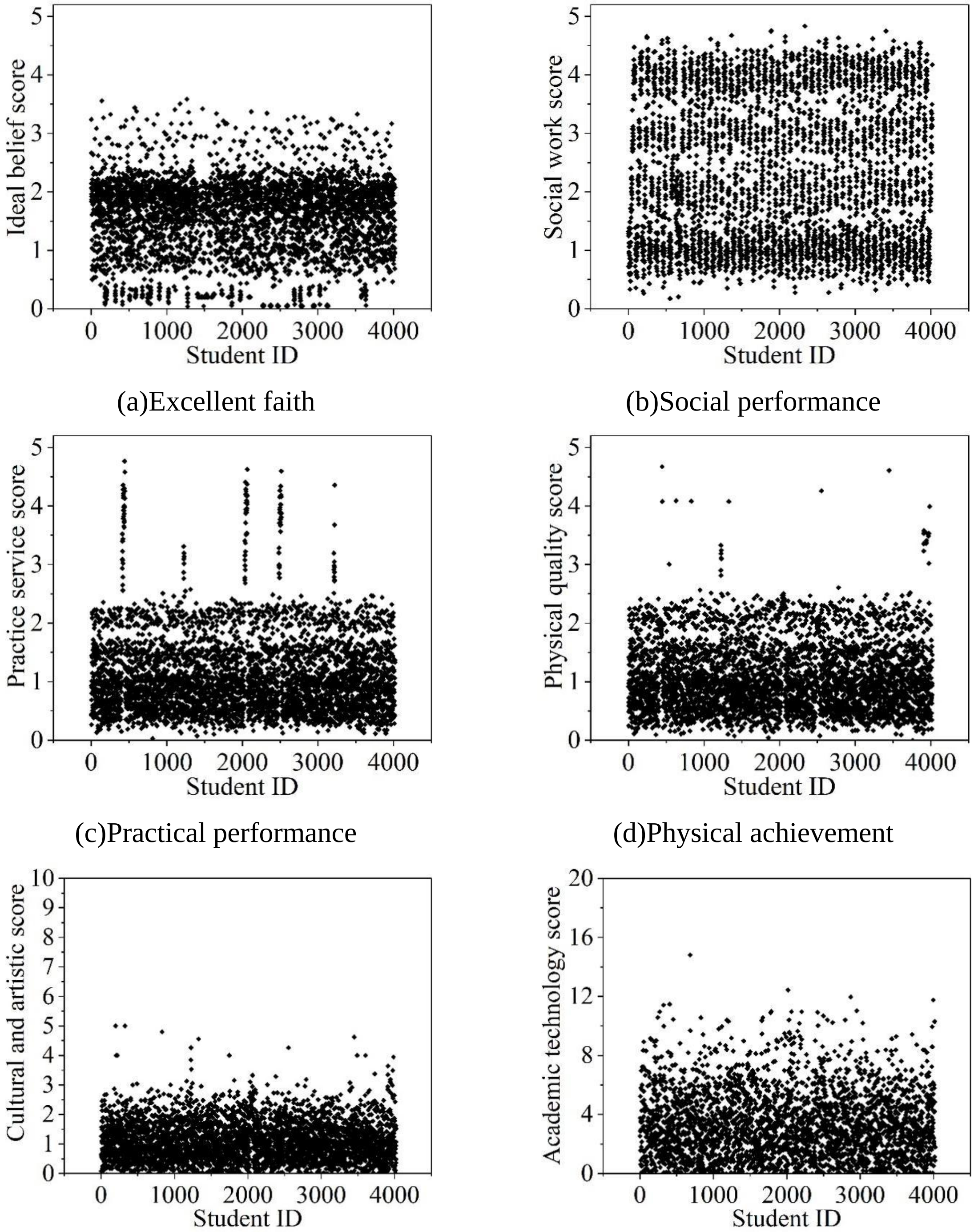
(a)Excellent faith (b)Social performance

(c)Practical performance (d)Physical achievement

(e)Cultural and artistic achievements (f)Academic achievement

Figure 1: The students' original data of the class is distributed

The scatter plot of the distribution of the pre-processed scores is shown in Fig. 2, and the graphs (a) to (f) are the ideal belief scores, social work scores, practical service scores, sports quality scores, cultural and artistic scores, and academic and scientific scores, respectively. It can be observed that after data preprocessing, the quality of the data is significantly improved, because a small number of students participate in fewer activities, so the score is only zero points, so there are a small number of data distributed near the axis. The next college student activity analysis is for the preprocessed data for cluster analysis, which not only meets the requirements of the algorithm but also meets the practical significance of the subject research.



(a)Excellent faith

(b)Social performance

(c)Practical performance

(d)Physical achievement

(e)Cultural and artistic achievements

(f)Academic achievement

Figure 2: After pre-processing, the distribution of results is distributed

2.2 Exploration of factors influencing youth entrepreneurial opportunities based on factor analysis

Factor analysis is a statistical analysis method that groups a series of variables with complex relationships from the correlation of indicators, and thus the same group of variables with higher correlation after grouping becomes a comprehensive common factor. The steps of the factor analysis method are shown in Figure 3.

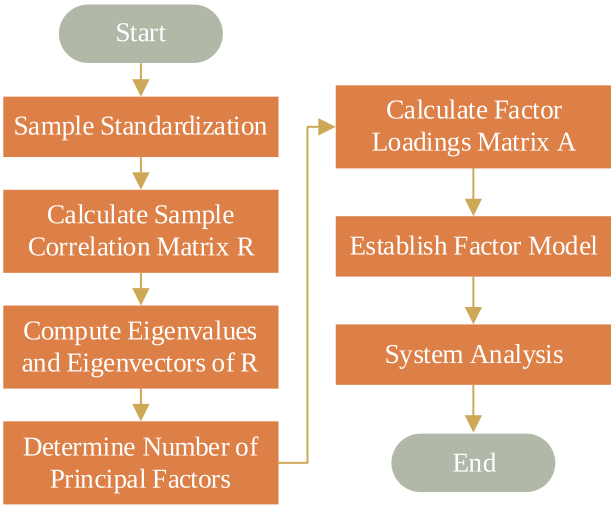


Figure 3: Flowchart of Factor Analysis Method

Let $X_i\left(i=1,2,\cdots,p\right)$ variable if it can be represented as:

$$X_i = \mu_i + a_{i1}F_1 + \cdots + a_{im}F_m + \varepsilon_i, \left(m \le p\right) \tag{1}$$

Or:

$$X - \mu = AF + \varepsilon \tag{2}$$

Among them:

$$x = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_p \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \cdots \\ \mu_p \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n1} & \cdots & a_{nm} \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_p \end{bmatrix} \tag{3}$$

We call $F_1, F_2, \cdots, F_p$ a common factor, and their coefficients are called loading factors, the larger its absolute value, the more closely related it is. ε_i is the special factor, which is the part that cannot be included by the previous m public factors. And it needs to be satisfied:

$$E\left(F\right)=0, E\left(\varepsilon\right)=0, Cov\left(F\right)=I_m \tag{4}$$

$$D\left(\varepsilon\right)=Cov\left(\varepsilon\right)=diag\left(\sigma_1^2,\sigma_2^2,\cdots,\sigma_m^2\right), \mathrm{cov}\left(F,\varepsilon\right)=0 \tag{5}$$

Factor analysis differs from regression analysis and principal component analysis in that regression factors have a very clear practical meaning; principal component analysis is only a variable transformation; and factors in factor analysis are abstract concepts and require the construction of factor models. Factor scores can be used to derive the importance indexes of different factors, which can be used for characterization, personality testing, product and behavior classification. The use of factor analysis in this system can accurately classify the questionnaire information into importance indexes, which is easy to classify the entrepreneurial ability of the youth.

2.3 Classification of young entrepreneurial groups based on improved k-means clustering

2.3.1 K-means cluster analysis methods

The K-means algorithm divides M data objects into k clusters, where k is the number of clusters predetermined by the user. Suppose $X=\{x_1,x_2,\cdots,x_m,\cdots,x_M\}$ is a set of data objects containing M data objects, each of which is N characterized by $F=\{f_1,f_2,\cdots,f_n,\cdots,f_N\}$, then each data object can be represented as $x_m=(x_{m1},x_{m2},\cdots,x_{mn},\cdots,x_{mN})$, where x_{mn} is the n th attribute value of the m th object. Let $C=\{c_1,c_2,\cdots,c_k,\cdots,c_K\}$ be a set of K clustering centers, $c_k=\{c_{k1},c_{k2},\cdots,c_{kn},\cdots,c_{kN}\}$ denote the k th clustering center, and c_{kn} denote the k th clustering center for the n th attribute.

Denote the dissimilarity measure between data object x_m and clustering center c_k as $diss(x_m,c_k)$. The smaller the value of $diss(x_m,c_k)$, the more likely it is that data object x_m belongs to clustering center c_k. Typically, denote $diss(x_m,c_k)$ as the Euclidean distance:

$$diss(x_m,c_k)=\sum_{n=1}^{N}d(x_{mn},c_{kn}) \tag{6}$$

where $d(x_{mn},c_{kn})=|x_{mn}-c_{kn}|^2$ is the dissimilarity between x_m and c_k on the n th attribute f_n.

According to Eq. (6), the optimal clustering result is found for any data object x_m and its corresponding clustering center c_k on the dataset such that the sum of the distances between the entire dataset and its clustering centers on the clusters is minimized, i.e:

$$Minimize\ S(U,c)=\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{n=1}^{N}u_{mk}\times d(x_{mn},c_{kn}) \tag{7}$$

Clustering centers for:

$$c_{kn}=\frac{\sum_{m=1}^{M}u_{mk}\times x_{mn}}{\sum_{m=1}^{M}u_{mk}},\ k=1,2,\cdots,K;\ n=1,2,\cdots,N \tag{8}$$

After many iterations until the center of the clusters stabilizes, indicating that the clusters have reached a full or partial steady state, the clustering process is terminated.

2.3.2 k-means cluster analysis method for fused coefficients of variation

The K-means algorithm treats all attributes equally and always gives all attributes the same weight during the clustering process. However, the effectiveness of data clustering often depends on a subset of attributes. Therefore, attribute selection is a widely noteworthy technique that removes irrelevant and redundant attributes to improve the quality of clustering results.

In summary, the purpose of attribute weighting for clustering is to assign appropriate weights to attributes based on how much they affect the quality of the clusters. Scholars have proposed many different methods for attribute weighting of clusters.

In this paper, we also use attribute weighting for clustering, where the coefficient of variation removes the effect of differences in units or means on the comparison of the degree of variation of two or more profiles. The effect of uncorrelated attributes on the clustering results is reduced by introducing a vector of coefficient of variation weights.

The coefficient of variation, also known as the coefficient of dispersion, is a statistical measure reflecting the distribution of data, which means the ratio of the indicator of variation of a set of data to its average indicator, i.e., the ratio of the standard deviation to the mean, noted as C.V.

If X is a random variable with probability density function $f(x)$, where x is a particular value of X, then the mean of the probability distribution of X is:

$$\mu = \int_{-\infty}^{\infty} x f(x) dx \tag{9}$$

The variance is:

$$\sigma^2 = \int_{-\infty}^{\infty} x^2 f(x) dx - \mu^2 \tag{10}$$

The coefficient of variation is:

$$CV = \sigma / \mu \tag{11}$$

Let $W = \{w_1, w_2, \cdots, w_n, \cdots, w_N\}$ be the set of weights of the N attributes of attribute set F, then the weight w_n of the nth attribute is:

$$w_n = \frac{CV_n}{\sum_{n=1}^{N} CV_n}, 0 \le w_n \le 1 \tag{12}$$

When attribute weights are considered, the dissimilarity measure between data object x_m and clustering center c_k is rewritten as:

$$CVdiss\left(x_m, c_k\right) = \sum_{n=1}^{N} CVd\left(x_{mn}, c_{kn}\right) \tag{13}$$

where $CVd\left(x_{mn}, c_{kn}\right) = w_n \left| \quad \right|^2$ is the dissimilarity between x_m and c_k on the nth property f_n.

Then:

$$Minimize\ S\left(U, c\right) = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{n=1}^{N} u_{mk} \times CVd\left(x_{mn}, c_{kn}\right) \tag{14}$$

Let U be a matrix of type $M \times K$ that records the relationships between objects and clusters, and $u_{mk} \in \{1, 0\}$ be an element of U that represents the relationship of the mth data object to the kth cluster. There:

$$\begin{cases} u_{mk} = 1, if \ \sum_{n=1}^{N} CVd\left(x_{mn}, c_{kn}\right) \le \sum_{n=1}^{N} CVd\left(x_{mn}, c_{\ln}\right) \\ \qquad for\ l = 1, 2, \cdots, K, and\ l \ne k \\ u_{mk} = 0, otherwise \end{cases} \tag{15}$$

If $u_{mk} = 1$, then x_m belongs to cluster C_k; if $u_{mk} = 0$, then x_m does not belong to cluster C_k.

3 Analysis of youth entrepreneurship under the high-skilled personnel training model

3.1 Construction of the evaluation index system of youth entrepreneurial capacity

3.1.1 Questionnaire design

On the basis of the existing structure of entrepreneurial ability, this paper combines the characteristics of youth itself and constructs the evaluation index system of youth entrepreneurial ability. The evaluation indexes mainly contain five aspects, such as knowledge, individual, opportunity, management and innovation, and each aspect contains several secondary indexes. In order to verify the reliability and validity of the evaluation index system, a questionnaire on youth entrepreneurial ability is designed. The questionnaire contains two parts, one is the basic situation survey, and the other is the survey on entrepreneurial ability. The questionnaire adopts Likert five-level scoring method.

The data of the questionnaire comes from a random sampling survey with six colleges and universities in the western region that are enrolled in college students as the main body of the survey. Among them, college A is financial institutions; college B is comprehensive institutions and former 985 institutions; college C and D are engineering institutions; college E is agricultural institutions; college F is teacher training institutions. 6 colleges and universities represent 5 different categories of institutions, which can be compared to derive the differences in the entrepreneurial ability of young people in different categories of institutions. A total of 4,020 questionnaires were distributed in this survey, and 2,950 valid questionnaires were actually recovered, with an effective recovery rate of 73.38%.

3.1.2 Factor analysis results

As there is a large degree of correlation between the indicators in the selection of evaluation indicators of entrepreneurial ability, the repetition of information will lead to the accuracy of the evaluation results being affected. Therefore, on the basis of comparing the advantages and disadvantages of various evaluation methods, the factor analysis method is chosen as the method of indicator selection. Factor analysis is a commonly used method for evaluating data indicators, which is able to use fewer factors to represent the relationship between more original variables with correlation. In this paper, SPSS22.0 software is selected to statistically analyze the obtained sample data and calculate the score of each common factor and the comprehensive score.

Using SPSS22.0 software to analyze the reliability of the questionnaire results, the Cronbach's α reliability coefficient was obtained as 0.888, with high reliability; KMO test and Bartllett's spherical test were conducted, and KMO = 0.882 was calculated, and Bartlett's spherical test chi-square value was 2439.275, and the significance p-value was 0.000, which is below the level of significance, indicating that the sample data is suitable for factor analysis.

The eigenvalues and variance contribution rates are shown in Table 1, according to the method of extracting the common factors with eigenvalues greater than 1, five factors with eigenvalues greater than 1 were extracted, and the variance contribution rates were 16.785%, 11.721%, 11.149%, 10.718%, and 9.186%, respectively, with a cumulative variance contribution rate of 59.559%, and the five proposed common factors, denoted by F1, F2, F3, F4, and F5, respectively.

Table 1: Eigenvalue and variance contribution

F	Pre-rotation factor			After rotation factor		
	Eigenvalue /%	Contribution rate /%	Cumulative contribution /%	Eigenvalue /%	Contribution rate /%	Cumulative contribution /%
F1	6.236	28.345	28.345	3.693	16.785	16.785
F2	3.005	13.659	42.005	2.579	11.721	28.506
F3	1.397	6.350	48.355	2.453	11.149	39.655
F4	1.356	6.164	54.518	2.358	10.718	50.373
F5	1.109	5.041	59.559	2.021	9.186	59.559

Factor analysis was performed using principal component analysis as well as maximum variance rotation orthogonal method. The initial factor loading matrix obtained through eigenvectors is prone to the phenomenon of mismatch in the size of the loadings between factors, resulting in little correlation, which is not conducive to the interpretation of the public factors, so the Kaiser standardized orthogonal rotation method was used to rotate the initial factor loading matrix orthogonally, and obtain the rotated factor loading matrix, and the rotated public factor loading matrix was shown in Table 2, with the indicators A1 to A4 combined into Indicators A1~A4 are combined into one factor, which is named as innovation factor; A5~A9 are combined into one factor, which is named as individual factor; A10~A13 are combined into one factor, which is named as opportunity factor; A14~A17 are combined into one factor, which is named as management factor; and A18~A22 are combined into one factor, which is named as knowledge factor. That is, the evaluation of youth entrepreneurial ability consists of five first-level indicators, and each first-level indicator contains several second-level indicators. Its indicator system is shown in Table 3.

Table 2: Coefficient of public factor score coefficient matrix

Index	Constituent				
	F1	F2	F3	F4	F5
A1	0.046	0.012	0.176	0.29	0.648
A2	0.009	0.190	0.094	-0.023	0.768
A3	0.019	0.012	0.394	0.135	0.618
A4	0.046	0.498	-0.138	0.024	0.504
A5	-0.014	0.568	-0.261	0.000	0.400
A6	0.104	0.545	-0.144	0.371	0.216
A7	-0.058	0.718	0.095	0.100	0.099
A8	0.065	0.649	0.310	0.066	0.000
A9	-0.008	0.693	0.295	0.205	-0.065
A10	0.106	0.273	0.552	0.151	0.194
A11	0.411	0.014	0.692	0.086	0.114
A12	0.333	-0.032	0.695	0.147	0.121
A13	0.276	0.186	0.559	0.354	0.035
A14	0.036	0.139	0.234	0.783	0.007
A15	0.26	0.071	0.181	0.789	0.101
A16	0.275	0.147	0.367	0.523	0.150
A17	0.235	0.299	-0.040	0.515	0.223
A18	0.790	0.009	0.208	0.024	0.005
A19	0.789	-0.036	0.229	0.061	0.036
A20	0.801	0.019	0.171	0.134	0.062
A21	0.793	0.028	0.125	0.180	0.000
A22	0.771	0.059	0.062	0.230	0.018

Table 3: Evaluation index system

Factor	Constituent index
Knowledge factor F1	Knowledge of entrepreneurship management, strategic management, human resource management, financial management and other relevant theories
	To understand the basic theoretical knowledge and advanced technology of the entrepreneurial industry
	Understand the relevant processes and how to work in the company and be able to develop the articles of association
	Knowledge of law, law, labor relations and other relevant laws
	To understand the government's rules and policies on entrepreneurship and identify policies that are good for their own businesses
Individual factor F2	I can get a lot of satisfaction after I finish my work
	Believe that you can accomplish your goals and be confident about the future of your future
	Never use false information to deceive others and be able to participate in time
	Even if my goals are difficult, I will stick to it
	Never shirking responsibility, dealing with work, learning perfection, and doing everything I can
Opportunity factor F3	Ability to accurately perceive and identify environments that are not met
	Ability to assess market potential, potential risks, and profitability
	Ability to identify all kinds of resources required for entrepreneurship
	Can effectively use resources to solve problems, can easily get help from the outside when difficult
Management factor F4	Be good at coordinating interhuman relationships and be able to mobilize the enthusiasm of people around them
	Be able to call and command others, inspire others, and make others willing to follow
	Able to identify various feasible schemes and based on resources and target planning strategies
	Can find learning, professional problems and questions to learn knowledge
Innovation factor F5	Dare to try unknown things, even if it doesn't have to do them good
	There is a strong willingness to change the existing ideas or practices and is willing to pay the price for reform
	In person, you dare to make different opinions and don't easily believe that you have not obtained scientific certification
	I hope to have the goals and ideals of work and think that life should be successful

The regression method was used to obtain the matrix of factor score coefficients, and the matrix of public factor score coefficients is shown in Table 4.

Table 4: Coefficient of public factor score coefficient matrix

Index	Constituent				
	F1	F2	F3	F4	F5
A1	-0.048	-0.168	-0.006	0.114	0.373
A2	-0.002	-0.044	0.000	-0.128	0.442
A3	-0.076	-0.135	0.175	-0.033	0.343
A4	0.065	0.165	-0.138	-0.099	0.234
A5	0.067	0.228	-0.194	-0.077	0.166
A6	0.041	0.184	-0.205	0.152	0.019
A7	-0.027	0.334	0.034	-0.080	-0.084
A8	-0.018	0.326	0.163	-0.143	-0.148
A9	-0.064	0.336	0.151	-0.033	-0.207
A10	-0.073	0.078	0.284	-0.078	0.015
A11	0.018	-0.019	0.332	-0.134	0.017
A12	-0.024	-0.064	0.343	-0.076	0.018
A13	-0.036	0.030	0.231	0.068	-0.082
A14	-0.124	-0.074	-0.005	0.459	-0.092
A15	-0.032	-0.112	-0.087	0.448	-0.019
A16	-0.021	-0.035	0.073	0.211	0.000
A17	0.040	0.029	-0.183	0.255	0.050
A18	0.265	0.028	-0.026	-0.124	-0.016
A19	0.255	-0.016	-0.019	-0.096	0.012
A20	0.263	0.002	-0.072	-0.050	0.013
A21	0.260	0.016	-0.104	-0.012	-0.025
A22	0.258	0.014	-0.15	0.027	-0.023

The scores of each common factor and the overall score were calculated using the regression method. The specific overall scores are shown in Table 5. Among the rankings of the comprehensive scores of young entrepreneurship capabilities of the 6 universities, university D in the engineering category has the strongest entrepreneurship ability, university A in the finance category follows, university C in the engineering category and university E in the agriculture category are in the middle position, university B in the comprehensive category ranks fifth, and university F in the teacher education category has the weakest entrepreneurship ability. The development of students' entrepreneurship capabilities in various aspects among the 6 universities is unbalanced. For example, students of university B in the comprehensive university rank first in innovation and creation, while in terms of individual personality traits, they are at the bottom.

Table 5: Public factor scores and rankings

N	F1	Rank	F2	Rank	F3	Rank	F4	Rank	F5	Rank	Tot	Rank
A	2.42	3	4.63	2	1.57	5	2.21	2	3.45	5	1.69	2
B	2.17	5	4.23	6	1.83	2	2.19	3	3.84	1	1.66	5
C	2.35	4	4.73	1	1.55	6	2.17	4	3.51	3	1.68	3
D	2.55	1	4.31	5	1.85	1	2.22	1	3.49	4	1.71	1
E	2.51	2	4.32	4	1.78	3	2.07	6	3.45	6	1.67	4
F	2.07	6	4.37	3	1.65	4	2.13	5	3.62	2	1.61	6

3.2 Analysis of the status of the dimensions of entrepreneurial ability

In this part, based on the data collected from the questionnaire survey, by calculating the mean, standard deviation and median of each dimension of entrepreneurial competence, and then judging the dimensions of entrepreneurial competence of young graduates accordingly, as shown in Table 6.

In terms of the mean value, the highest mean value among the dimensions is organizational management ability, which is 3.856, and the lowest is entrepreneurial knowledge ability, which is 3.561.The mean values of the dimensions are between 3.561-3.856, and in descending order, the mean values of the dimensions are organizational management ability (3.856), innovation and creativity ability (3.794), opportunity exploration ability (3.789), individual personality traits (3.711), individual personality traits (3.711), individual personality traits (3.789), and individual personality traits (3.789). 3.711), and entrepreneurial knowledge ability (3.561).

In terms of standard deviation, the standard deviation of the dimensions ranged from 0.743 to 1.087, and the standard deviation in descending order was entrepreneurial knowledge competence (1.087), opportunity discovery competence (0.825), individual personality traits (0.812), organizational and management competence (0.755), and innovative and creative competence (0.743). The median of all dimensions of entrepreneurial competence ranged from 3.755 to 4.002, with opportunity exploration ability and organizational management ability being the highest with the same value of 4.002, and entrepreneurial knowledge ability, individual personality traits and innovation and creativity ability being the lowest with the same value of 3.755.

The above data show that young graduates perform best in organizational management ability, better in individual personality traits, opportunity exploration ability and innovation and creativity ability, but worse in entrepreneurial knowledge ability, the average value is only 3.561, which reflects the lack of entrepreneurial knowledge ability of young graduates and the fact that colleges and universities have not yet provided young graduates with effective guidance on career planning, and this should be paid attention to.

Table 6: The state of entrepreneurship

Name	Sample size	Mean	Standard deviation	Median
Entrepreneurial knowledge	2950	3.561	1.087	3.755
Individual personality traits	2950	3.711	0.812	3.755
Opportunity	2950	3.789	0.825	4.002
Organizational management	2950	3.856	0.755	4.002
Creative ability	2950	3.794	0.743	3.755

3.3 Cluster analysis and chi-square analysis

Figure 4 is a three-dimensional presentation of the three achievements of ideal beliefs, social work, and practice services, from which we can observe that the orange circle icon corresponds to the category with the largest number of people, the blue circle icon corresponds to the category with a medium number of people, and the gray circle icon corresponds to the category with the smallest number of people. In general, most of the data are concentrated around the axes, and there is a clear correlation between social work and practical services, while the correlation between ideal beliefs and social work, and ideal beliefs and practical services is not obvious.

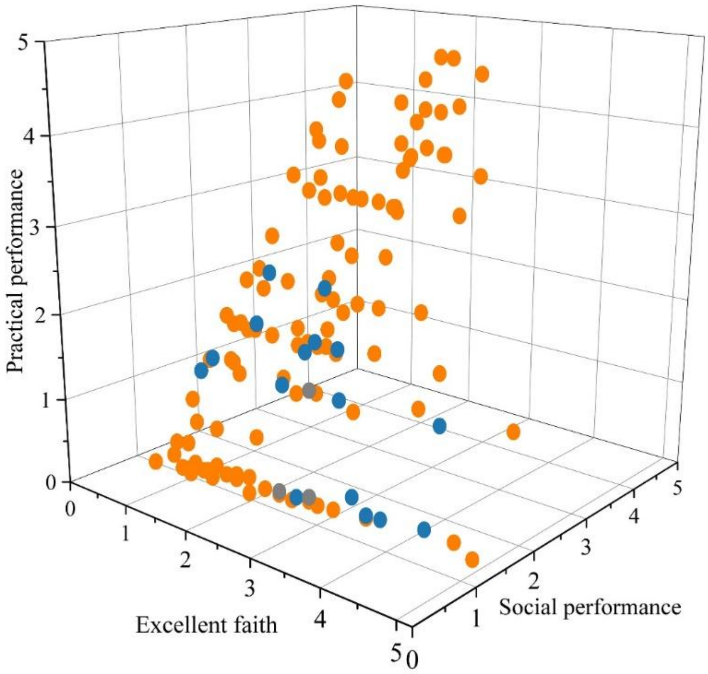


Figure 4: Ideal belief, social work, and practice service 3d display

Figure 5 is a three-dimensional presentation of the three scores of sports quality, culture and art, and academic science and technology, from which it can be observed that the orange circle icon corresponds to the category with the highest number of people, the blue circle icon corresponds to the category with a medium number of people, and the gray circle icon corresponds to the category with the lowest number of people. From the overall point of view, most of the scatter points are concentrated near the coordinate axes. Also from the range of the axes we can observe that the students' performance in arts and culture and academic science and technology is on the high side, while there is no significant correlation between the three.

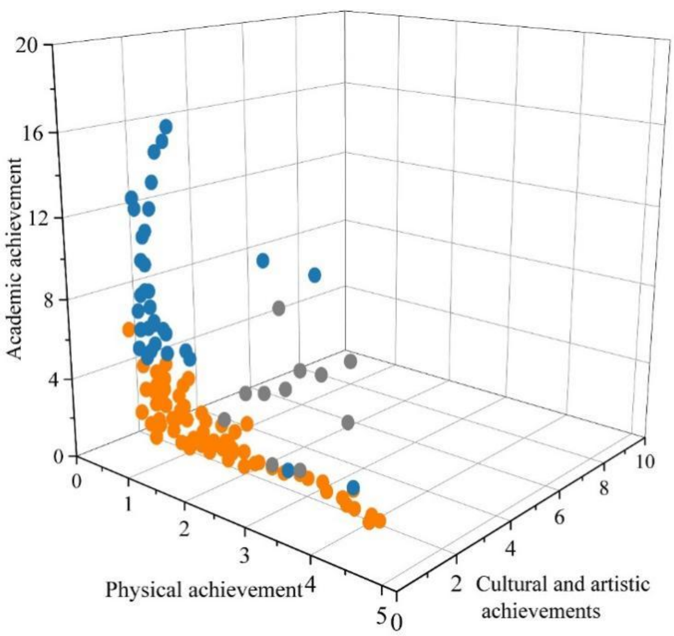


Figure 5: 3D display of sports quality, cultural art and academic science

Table 7 shows the clustering analysis table generated using K-means clustering analysis, from which it can be visualized that three clustering categories were generated, with sample sizes (N) of 845, 435, and 815 for each category, respectively. Comparatively, the clustering category Cluster 1 has the highest sample size of 40.334%, followed by Cluster 3 with 38.902%, while Cluster 2 has the least sample size of 20.764%.

Table 7: Cluster classification

Cluster class	Frequency	Proportion/%
Cluster 1	845	40.334
Cluster 2	435	20.764
Cluster 3	815	38.902
Total	2095	100.000

After analyzing the ANOVA of the three categories of samples generated by K-means clustering analysis, it can be clearly seen that the three categories of samples are different on the five components of entrepreneurial competence, and the results of the ANOVA difference comparison of the clustering categories are shown in Table 8. It can be seen that there is a significant difference between the three types of clustered samples on the five elements (entrepreneurial knowledge ability, individual personality traits, opportunity exploration ability, organizational management ability, innovation and creativity ability). The characteristics of these three types of samples can be analyzed and classified into "strong entrepreneurial ability", "weak entrepreneurial ability" and "medium entrepreneurial ability".

Summarizing the above analysis, the characteristics of these three types of samples can be clearly distinguished and are in line with the current reality of the entrepreneurial ability of young graduates, which ultimately indicates that the clustering effect is better. In addition, those with strong entrepreneurial ability accounted for 40.334%, those with medium entrepreneurial ability accounted for 38.902%, and still 20.764% were those with weak entrepreneurial ability. Therefore, although the overall status of entrepreneurial ability of young graduates is currently at the medium to high level, it does not meet expectations. The reason why the problem exists is that there is a discrepancy between reality and expectations. The problems with the entrepreneurial ability of young graduates are as follows: As young graduates who are part of the new era and have received higher education, they should possess high-level entrepreneurial capabilities and meet the expectations for high-level entrepreneurial capabilities. However, according to the survey, the actual situation is that the entrepreneurial ability of young graduates is generally at a medium to upper level, but there are still 20.764% who have weak entrepreneurial capabilities. The existing problems should attract the attention of universities, relevant departments, and society. *p<0.05, **p<0.01.

Table 8: Comparison results of variance analysis of cluster variance analysis

	Cluster 1	Cluster 2	Cluster 3	F	P
	Strong employability	Weak employment ability	Medium man		
Entrepreneurial knowledge	4.47±0.45	2.27±0.67	3.31±0.84	312.181	0.000**
Individual personality traits	4.34±0.42	2.73±0.62	3.56±0.62	248.858	0.000**
Opportunity	4.44±0.37	2.72±0.63	3.67±0.55	331.548	0.000**
Organizational management	4.42±0.41	2.92±0.61	3.77±0.56	235.985	0.000**
Creative ability	4.68±0.31	3.76±0.42	4.25±0.42	170.971	0.000**

4 Conclusion

Based on the data collection of young graduates' entrepreneurial ability, this study examines the current situation of youth entrepreneurial ability, its structural characteristics and its association with entrepreneurial opportunities and employment paths in the context of the era of high-skilled personnel training.

This paper constructs the evaluation index system of youth entrepreneurial ability to comparatively analyze and evaluate the entrepreneurial ability of youth in six universities. Youth entrepreneurial ability can be effectively explained by five common factors, such as entrepreneurial knowledge ability, individual personality traits, opportunity exploration ability, organizational management ability and innovation and creation ability, with a cumulative variance contribution rate of 59.559%. The overall performance of students in engineering colleges is more prominent, while the overall performance of teacher training colleges is weaker, suggesting that universities should pay attention to the integration of interdisciplinary abilities and the shaping of individualized abilities when guiding students to develop employment paths, avoiding the tendency to focus on professionalism rather than literacy or skills rather than personality.

The results of the current status and variability analysis of entrepreneurial competence of young graduates showed that among the scores of entrepreneurial competence dimensions, entrepreneurial knowledge competence had the lowest score and organizational management competence had the highest score. The k-means cluster analysis method based on the fusion coefficient of variation classified the young graduates into three cluster samples of strong entrepreneurial ability, medium entrepreneurial ability and weak entrepreneurial ability. Among them, 40.334% were strong entrepreneurial competence holders, 38.902% were medium entrepreneurial competence holders and 20.764% were weak entrepreneurial competence holders. It illustrates that although the youth entrepreneurial ability generally shows a medium level, the internal differences are more obvious, and there are a certain number of entrepreneurial ability short board groups. In view of the reality of weak entrepreneurial expertise of youth, colleges and universities should popularize the curriculum of entrepreneurship education to provide professional theoretical support for college students' entrepreneurship. In the high-skilled neighborhood, the design of complex jobs can help young people to continuously improve their entrepreneurship-related abilities in employment, forming a virtuous cycle of mutual promotion of employment and entrepreneurship.

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