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Article

Research on the Nurturing Role of College Students' Competitions Based on the Ability Portrait of Discipline Competitions--Taking K-means Clustering Algorithm as an Analyzing Tool

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Abstract: In the context of the deepening national strategy of integrating education, science and technology with talents, academic competitions have become the core carrier of practical education in higher education. This paper proposes a concept of individual competence portrait of academic competitions and constructs a competence framework containing seven dimensions by synthesizing hierarchical analysis, principal component analysis and K-means clustering algorithm. Through descriptive statistics, Pearson correlation analysis and regression analysis, the positive associations between academic competitions and their related dimensions were initially revealed. The empirical analysis shows that the framework has good reliability and validity and can effectively identify students' ability characteristics. Discipline competitions have a significant positive effect ($p<0.005$) on learning and analyzing ability, evaluating and innovating ability, and comprehensive practice ability. And based on the results of the study, we propose countermeasures for academic competitions to promote college students' ability.

Keywords: academic competitions; ability portrait; K-means clustering algorithm; ability characteristics

1. Introduction

In today's increasingly competitive society, cultivating high-caliber, innovative talent has become a key objective of education [1–2]. As a unique educational activity, academic competitions provide students with a platform to showcase their talents and hone their skills, playing an indispensable role in talent development [3–4]. They not only stimulate students' interest in learning and foster innovative thinking but also cultivate their teamwork spirit, practical skills, and problem-solving abilities [5–6]. In recent years, universities have leveraged the competitive, practical, and specialized nature of academic competitions, along with the prestige associated with winning, to comprehensively enhance the overall quality of college students [7]. However, in practice, these efforts have not significantly contributed to the comprehensive improvement of students' overall quality, and the effectiveness of competition-based education remains limited. To address this, the concept of academic competition competency profiling has gradually gained traction.

Competition competency profiling represents a key manifestation of digitalization in education during the era of big data. By utilizing big data technologies to analyze and mine vast amounts of student data, it reveals students' characteristics and behavioral patterns. This helps universities better understand students' subject-specific abilities and needs, thereby providing personalized educational services and support for competition-based education [8–11]. By analyzing these profiles, institutions can develop teaching strategies and personalized educational plans tailored to different student groups, thereby addressing their diverse learning needs and interests [12–14]. Additionally, universities can use these profiles to identify the causes of underperformance and potential academic issues, enabling them to take timely measures to provide assistance and support, thereby better promoting the development of competition-based education.

This paper proposes an analytical framework called "Personal Academic Competition Ability Portrait". This framework utilizes a systematic indicator system and clustering algorithms as tools to integrate the ability portrait into the academic competition evaluation system. This framework explores a paradigm shift, moving from "result-oriented" to "process tracking", from "single-dimensional measurement" to "multi-dimensional analysis", and from "empirical judgment" to "data-driven". At the same time, through the comprehensive analytic hierarchy process, principal component analysis, and K-means clustering algorithm, it automatically identifies students' ability patterns from the massive competition data sets, thereby providing data-driven precise strategies for higher education institutions to cultivate talents through academic competitions.

2. Related algorithms

2.1. Cluster analysis

Cluster analysis is different from classification analysis, which is to cluster data objects based on their own characteristics without knowing the number of categories and classifications. Because cluster analysis is based on the intrinsic characteristics of the data object for classification, do not need to specify the number of categories and classification labels, so different researchers on the same kind of data clustering, the results may be different. The definition of cluster analysis is as follows:

Suppose $w = \{x_1, x_2, \cdots, x_n\}$ is the sample dataset, and $c_1, c_2, \cdots, c_k$ is the partitioned class clusters, where $x_i = (x_{i1}, x_{i2}, \cdots, x_{im})^T$, if satisfied:

(1) $c_i \neq \phi, i = 1, 2, \cdots, k$;

(2) $\bigcup_{i=1}^{k} c_i = w$;

(3) $c_i \cap c_j = \phi, i, j = 1, 2, \cdots, k$ and $i \neq j$.

Where condition (1) ensures that none of the categorical sets obtained from clustering is an empty set, i.e., it contains at least one element; condition (2) ensures that each element in the sample data set can be classified into different class clusters; and condition (3) restricts that each data sample can only be classified into a unique class cluster, i.e., each categorical set exists independently.

In order to carry out reasonable clustering division of data with different shapes, types and sizes, researchers at this stage have proposed a variety of cluster analysis algorithms, but still have not found a refined clustering algorithm that can be universally applied. Therefore, when performing clustering, it is necessary to choose a most suitable clustering algorithm according to the characteristics of the data itself and the purpose of clustering.

2.2. K-means clustering algorithm

K-means clustering algorithm is a more classical clustering algorithm in cluster analysis. In the process of practical application, it mainly takes k as a parameter, and at the same time, it divides n objects into k clusters, and the similarity of all the data within the clusters takes a relatively high value. K-means clustering algorithm's main advantage is that it can deal with large-scale data, the overall scalability is better, while the computational speed is also faster.

In the K-means clustering algorithm, the similarity measure is carried out through the Euclidean distance, and the sum of squared errors is selected as the objective function to evaluate the clustering results of the ability characteristics of the disciplinary competitions. The Euclidean distance $d(x, y)$ between two random data points is given by formula (1):

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{1}$$

where x_i and y_i represent the i th data point in the data set x and data set y, respectively; and n represents a constant.

The corresponding formula for the error sum of squares is given through equation (2):

$$SSE = \sum_{i=1}^{n} \sum_{j=1}^{n} |d(x, y)|^2 \tag{2}$$

where j represents the number of data points.

The detailed operational flowchart of the K-means clustering algorithm is given in Figure 1;

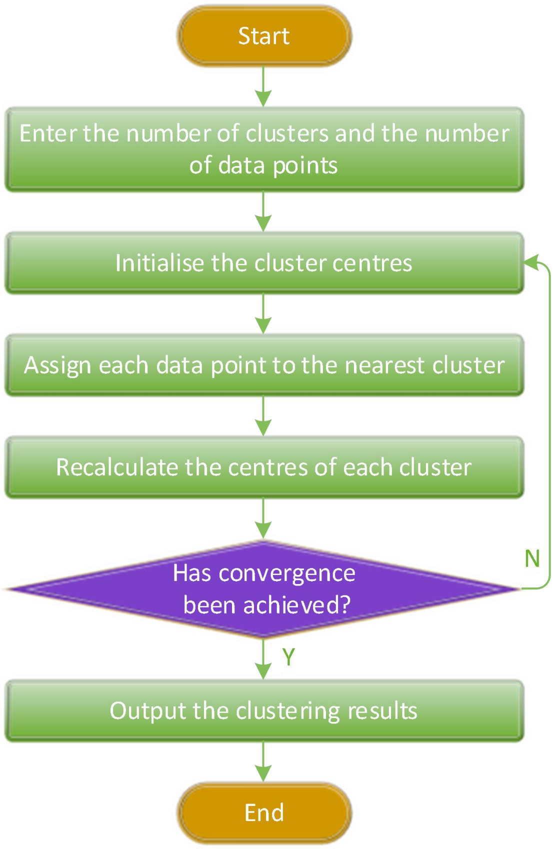

Figure 1. Operation flowchart of K-means clustering algorithm

Combined with the above figure, the following classification process is carried out by K-means clustering algorithm on the characteristics of the ability of subject competitions, and the detailed operation steps are shown as follows:

(1) In the sample set, randomly select k objects, which will be set as the center of the initial cluster;

(2) Calculate the distance $d(u,m)$ from each u to the center of the k clusters in the data set by using equation (1);

(3) Obtain the minimum distance $d(u,m)$ of each object p and divide p into the same cluster as m;

(4) Perform the traversal process for all objects, and after completing the traversal, it is also necessary to recalculate the value of m and set it as the center of a brand new cluster;

(5) Re-assign the objects in the whole data set to the cluster with the highest degree of similarity, and at the same time, repeat the above steps to ensure that the obtained sum-of-squares error is the smallest, and ultimately realize the clustering of the characteristics of the ability of subject competitions.

2.3. Clustering effectiveness evaluation methods

The goal of clustering is to divide the data by selecting a similarity measure that makes the data in the same cluster as similar as possible. In order to determine the effectiveness of clustering, clustering validity evaluation indexes have emerged. At present, there are a variety of clustering validity evaluation indexes, which can be roughly divided into two categories: internal validity indexes and external validity indexes.

2.3.1. Internal validity indicators

The internal validity index does not utilize any reference model and is obtained from its own clustering results, which are mainly based on the geometric structure information of the dataset to evaluate the clustering division results in terms of tightness, separation and overlap. The most commonly used internal validity indicators are as follows:

(1) CH indicator

The larger its value, the better the clustering effect. It is defined as follows:

$$CH = \frac{Tr(S_b)/k-1}{Tr(S_w)/n-k} \tag{3}$$

where n denotes the number of clusters, k denotes the current number of categories, and $Tr(S_b)$, $Tr(S_w)$ denote the traces of inter-class and intra-class deviation matrices, respectively.

(2) Dunn's indicator

Also known as Dunn indicator, the larger its value, the better the clustering effect. It is defined as follows:

$$DVI = \frac{\min\limits_{0<m\neq n<k}\left\{\min\limits_{\substack{\forall x_i\in\Omega_m\\ \forall x_j\in\Omega_n}}\left\{\left\|x_i-x_j\right\|\right\}\right\}}{\max\limits_{0<c<n<k}\max\limits_{0<c<n<k}\left\{\left\|x_i-x_j\right\|\right\}} \tag{4}$$

(3) DB index

Also known as Davidson's Boulding Index, the larger its value, the better the clustering effect. It is defined as follows:

$$DB = \frac{1}{k}\sum_{i=1}^{k}\max_{j=1}\left(\frac{\overline{C_i}+\overline{C_j}}{\left\|w_i-w_j\right\|_2}\right) \tag{5}$$

where $\overline{C_i}$ and $\overline{C_j}$ denote the average intra-class distances of the i th and j th classes, respectively, and $\left\|w_i-w_j\right\|$ denotes the distance between the two classes of the i th and j th classes.

2.3.2. External validity indicators

The external validity indicator is to compare the clustering results obtained by the algorithm with the real classification results to judge the clustering effectiveness of the algorithm when the real classification of the data is known. Suppose $L=\{l_1,l_2,\cdots,l_k\}$ is the clustering result obtained by the algorithm, and $S=\{s_1,s_2,\cdots,s_p\}$ is the real classification result. Results.

The a in the Rand index and Jaccard index is the number of pairs of individuals that belong to the same category in both S and L , b is the number of pairs of individuals that belong to the same category in S but not in L , c is the number of pairs of individuals that belong to the same category in L but not in S , and d is the number of pairs of individuals that do not belong to the same category in both classifications. Commonly used external validity indicators are as follows:

(1) Acc indicator

Acc index is also known as the accuracy index, the larger the value, indicating that the number of samples are correctly divided, the better the clustering effect. The definition is as follows:

$$Acc = \frac{N_{cor}}{N} \tag{6}$$

where N_{cor} denotes the number of samples that were correctly divided in this division. N denotes the total number of samples.

(2) Rand index

Rand index is also known as Rand index, the larger the value, the more the number of samples are correctly divided, the better the clustering effect. The definition is as follows:

$$Rand = \frac{a+b}{a+b+c+d} \tag{7}$$

(3) Jaccard index

Jaccard index is also known as Jaccard index, the larger the value, the more the number of samples are correctly divided, the better the clustering effect. The definition is as follows:

$$Jaccard = \frac{a}{a+b+c} \tag{8}$$

2.4. Similarity Measures

2.4.1. Distance measurement

The distance metric is used to measure the distance that individuals exist in space. A greater distance indicates a greater difference between individuals. Assuming that $x=\{x_1,x_2,\cdots,x_m\}$, and $y=\{y_1,y_2,\cdots,y_m\}$ are the samples in D, denote $d(x,y)$ is the distance between x, y. The ways of calculating $d(x,y)$ by distance measures are categorized as follows:

(1) Euclidean distance:

$$d(x,y)=\|x-y\|=\sqrt{\sum_{i=1}^{m}(x_i-y_i)^2} \tag{9}$$

(2) Absolute distance:

$$d(x,y)=\sum_{i=1}^{m}|x_i-y_i| \tag{10}$$

(3) Chebyshev distance:

$$d(x,y)=\max_i|x_i-x_j| \tag{11}$$

(4) Nominal distance:

$$d(x,y)=\left(\sum_{i=1}^{n}|x_i-x_j|^m\right)^{\frac{1}{m}} \tag{12}$$

2.4.2. Correlation coefficient measures

The correlation coefficient is another way to measure the similarity of samples, and by calculating the size of its value you can determine the degree of correlation between two samples. The following are two methods commonly used to calculate the correlation coefficient:

(1) Cosine of angle method

The cosine of the angle between two vectors in the vector space is used to measure the degree of similarity between two samples, i.e., the cosine of the angle method. The closer the value is to 1, the more similar the two samples are. The specific formula is:

$$\cos(x,y)=\frac{\sum_{i=1}^{m}x_iy_i}{\sqrt{\sum_{i=1}^{m}x_i^2}\sqrt{\sum_{i=1}^{n}y_i^2}} \tag{13}$$

(2) Pearson correlation coefficient

Pearson correlation coefficient is a statistical measure used to reflect the degree of similarity between two variables. The range of values is $[-1,1]$, the larger its absolute value, the stronger the correlation between the two samples. The specific formula is:

$$p(x,y)=\frac{\sum_{i=1}^{m}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{m}(x_i-\overline{x})^2\sum_{i=1}^{m}(y_i-\overline{y})^2}} \tag{14}$$

3. Study design

3.1. Construction of the indicator system

Utilizing the inherent characteristics of engineering students' competition practice and based on the logic of competence development, this study establishes a multilevel disciplinary competition evaluation framework that includes a target layer, a standard layer, an indicator layer and a description layer. The framework emphasizes the comprehensive evaluation of students' three core competencies: learning ability, evaluation ability and practical application ability. At the theoretical level, the framework draws on the theory of competency-based education and Bloom's taxonomy of educational objectives, and establishes three standard layers of learning and analyzing ability, evaluation and innovation ability, and comprehensive practical ability based on the chain of "cognition-thinking-practice" competency development. At the operational level, a comprehensive evaluation system has been developed through a systematic review of the educational applications of discipline competitions and multiple rounds of consultation with an expert group consisting of college competition administrators, instructors and industry professionals.

The evaluation index system of disciplinary competition competence is shown in Table 1, which consists of three standard levels and seven indicator levels, and has gone through initial index drafting, expert review and consistency verification. Learning and analytical ability is the foundation, focusing on the mastery of knowledge and the initial discovery of problems; evaluation and innovation ability is the core, emphasizing analysis and innovative thinking; and comprehensive practice ability is the ultimate goal, prioritizing the transformation of results, teamwork and communication skills. These three levels are progressive, and together they constitute a systematic evaluation framework for competence in disciplinary competitions.

Table 1. Evaluation Indicator System for Academic Competition Competence

Policy Level	Indicator Level	Description Layer
A: Learning Analysis Skills	A1: Knowledge Acquisition Ability	The ability to identify and raise issues
	A2: Ability to identify problems	The ability to obtain information and gather data
B: Evaluating Creative Ability	B1: Problem Identification Ability	The ability to analyze and reflect on the research subjects
	B2: Innovative Thinking Skills	The ability to propose new ideas, methods, and results
C: Comprehensive Practical Skills	C1: Problem-Solving Ability	The ability to translate research findings into practical applications
	C2: Team Collaboration Skills	The ability to collaborate as a team during the organization of competitions
	C3: Communication and Expression Skills	The ability to articulate the processes and outcomes of scientific research activities

3.2. Competitiveness factors

In order to meet the requirements of K-mean clustering for low-dimensional and highly discriminative features, and at the same time to deeply excavate the intrinsic structure among the indicators, this study uses PCA factor analysis for dimensionality reduction on the basis of the established indicator system. The calculated KMO value is 0.843, the Bartlett's test result is highly significant ($P<0.001$), and the cumulative variance contribution rate reaches 82.6%, indicating that the factor structure is robust and can effectively capture the information on students' competitiveness reflected by the seven secondary indicators.

According to the loadings of the indicators in the common factors and their practical significance in discipline competitions, the four common factors were named as shown in Table 2.

Table 2. Setting of Competition Ability Factors

Factor	Factor Name	Main Relevant Indicators	Factor Content
F1	Professional Support Level	A1: The ability to acquire knowledge	It reflects the balance between students' own efforts in knowledge acquisition, information gathering, and problem understanding, and the level of

		A2 The ability to identify problems	support provided by school-based professional education—a concentrated manifestation of their competitive knowledge base.
F2	Team Contribution	C2 Team Assistance Capability C3 Communication Skills	Measures students' collaboration skills, communication efficiency, and actual contribution to team outcomes in a team environment, with some cross-loadings across other indicators.
F3	Competition-level difficulty	B1 Ability to identify problems B2: Innovative Thinking Ability C1: Problem-solving ability	The key factor in assessing the challenge level of a competition is its representation of the students' participation tier, technical difficulty, and the requirements for higher-order thinking.
F4	The Impact of Competitions	B2: Innovative Thinking Ability C1: Problem-solving ability	It reflects the comprehensive performance of the participating projects in terms of innovation, practical value, and social impact, serving as an external manifestation of the competition's effectiveness.

3.3. Calculation of indicator weights

The subjective weights were determined using the principal component analysis (AHP) method. Twelve experts were invited to make pairwise comparisons of the three criterion levels and their subordinate indicator levels, construct judgment matrices, calculate weight vectors, and conduct consistency tests (CR<0.1). The geometric mean method was used to summarize the clustering judgment results as shown in Table 3, which resulted in the subjective weights of each indicator: learning and analyzing ability (0.25), evaluating and innovating ability (0.4), and comprehensive practice ability (0.35). From the weight distribution of each index level, the innovative thinking ability (0.22) and problem solving ability (0.15) have the highest weights, reflecting that the competition attaches great importance to innovation and practical application ability.

Table 3. The weight results of the first-level indicators

Index	Weight	Core Association	Result
Learning Analysis Ability (A)	0.25	Related Knowledge Acquisition	The weight is low; the course provides supplementary training.
Judge creativity (B)	0.40	Central Position; Corresponding to New Engineering Competencies	Core of competition evaluation; focus on cultivation
Comprehensive Practical Skills (C)	0.35	Related Knowledge Application	Key Evaluation Criteria for Competitions; Focus on Cultivation

The portfolio weights were determined using the multiplicative synthesis method, calculated using the formula:

$$W_j^{com} = \frac{W_j^{AHP} \times W_j^{PCA}}{\sum_{j=1}^{n} W_j^{AHP} \times W_j^{PCA}} \tag{15}$$

This approach synthesized the two weights to produce the final combined weights for each secondary indicator as shown in Table 4. And based on the matrix of factor analysis component coefficients, the scores F1, F2, F3 and F4 were calculated for each student on the four factors.

Table 4. Weightings of the secondary indicator combinations

Primary Indicator	Secondary Indicator	Combination weight	Load value
A: Learning Analysis	A1: The ability to acquire knowledge	0.14	The load of Principal Component 3 is 0.68.

Skills	A2 The ability to identify problems	0.11	The load of Principal Component 2 is 0.79.
B. Evaluating Creative Ability	B1 Ability to identify problems	0.18	Principal Component 1 load factor: 0.87
	B2: Innovative Thinking Ability	0.22	Principal Component 1 load factor: 0.91
C: Comprehensive Practical Skills	C1: Problem-solving ability	0.15	Principal Component 1 load factor: 0.83
	C2 Team Assistance Capability	0.10	Principal Component 2 load factor: 0.75
	C3 Communication Skills	0.10	Principal Component 2 load: 0.41. The load of Principal Component 3 is 0.39.

3.4. K-means clustering algorithm design

The K-means algorithm was chosen as a clustering tool mainly because it has the advantages of low computational complexity, interpretability, and suitability for large datasets. The algorithm aims to classify n data points into k clusters by minimizing, the sum of the squares of the distances from each point to the corresponding cluster center. The specific formula is as follows:

$$WCSS = \sum j = \sum_{k}^{1} {}_{x_i \in C_j} \left| x_i - \mu_j \right|^2$$

Here, $x_i \in \mathbb{R}^4$ denotes the four-dimensional factor vectors in this study, and μ_j denotes the center of clustering for the j th category. A combination of elbow rule and silhouette coefficient is used to select the value of k corresponding to the elbow inflection point of the curve with the highest silhouette coefficient.

Both the elbow rule and the silhouette coefficient indicate that the silhouette coefficient peaks at 0.45 when K=4 and the SSE decreases at a slower rate. Therefore, K=4 gives the best clustering results. The clustering quality was comprehensively evaluated using the silhouette coefficients and the Davis-Boulding (DBI) index. Based on the different characteristic patterns of the four clustering centers in each factor, they can be classified into four types Total Leadership, Teamwork, Track-Specific Excellence, and Potential Growth, as shown in Table 5.

Table 5. Types and Characteristics of Competition Ability Cluster Profiles

Cluster type	Factor Pattern Feature	description
The All-Round Leader	All four factor scores were high, with professional support (F1) and competition influence (F4) standing out prominently.	It holds a comprehensive lead in competitive capabilities, serving as the core leader in high-level competitions.
Team Collaborative	Team contribution (F2) is significantly higher than other factors.	Skilled in communication and collaboration, playing a key role in team-based competitions
Track-Specific Attack Strategy	High scores were achieved in both competition difficulty level (F3) and competition influence (F4).	Dare to participate in high-difficulty competitions, demonstrating strong problem-solving and innovative capabilities.
Potential Growth Type	The scores of all factors are relatively low, but the professional support level (F1) is acceptable.	Their competitive abilities need improvement; they are the key targets for focused cultivation and guidance.

4. Empirical analysis

4.1. Data collection and processing

This study investigated 2,847 undergraduate students who participated in disciplinary competitions at Zhejiang Normal University between 2023 and 2025. Data were collected through the university's academic affairs system and competition management platform, including course grades, competition records (participation history, award level, team roles), student development indicators (research papers, patents, entrepreneurial projects), and behavioral data (training attendance, lab usage time). After anonymization, the analysis showed a significant correlation between factor scores and competition awards (Pearson's coefficient between 0.71 and 0.89, $P < 0.005$).

4.2. Cluster characterization

Percentage scores for the seven dimensions (A1-C3) were entered into the K-means algorithm (K=4) for cluster analysis. One-way ANOVA showed that there was a significant difference between the four groups in the ranking of competition awards ($F=79.36$, $p<0.001$), and the agreement rate with teachers' qualitative evaluations was 83.2%, which proved the validity of the characterization method. In addition, the cluster centers and feature portraits of the four disciplinary competition competencies are shown in Table 6, and the distribution of the scores of the four cluster centers on all seven dimensions presents obvious features.

Table 6. Clustering Centers and Features of the Four Competency Portraits

Dimension	The All-Round Leader	Team Collaborative	Track-Specific Attack Strategy	Potential Growth Type
A1 Knowledge Acquisition	82.3	78.6	65.2	71.4
A2 Information Processing	79.8	81.2	63.7	68.9
B1 Analysis and Judgment	83.5	85.4	67.8	64.3
B2 Innovative Thinking	78.9	91.6	52.3	58.7
C1 Technology Implementation	85.2	72.4	88.7	55.2
C2 Team Collaboration	81.7	63.5	76.8	62.1
C3 Outcome Expression	80.4	75.8	71.3	56.8

Based on the morphological characteristics depicted in the seven-dimensional radar chart, four different student types can be classified, as shown in Table 7. 9.1% (259) of the students were overall leaders, which led in all four factors. These students frequently served as team leaders and demonstrated excellent competition skills, with a national award rate of 68.9%. Teamwork types, at 28.4% (809), excelled in team contributions and demonstrated strong coordination and collaboration skills in developing original solutions. The Track Professional type, at 24.6% (700), is characterized by active participation in high-level competitions, outstanding practical skills, and remains the backbone of the competition team despite slightly lower team-related factors. The Potential Growth type accounted for 37.9% (1,079 students) and performed below average in all areas; these students have limited competition experience but have a solid theoretical foundation and are prime candidates for targeted development programs.

Table 7. Factor Center Scores and Proportions for Four Student Groups

Cluster type	Professional Support Level	Team Contribution	Competition-level difficulty	The Impact of Competitions	Proportion
The All-Round Leader	1.18	0.87	1.21	1.33	9.1%
Team Collaborative	0.24	1.24	-0.15	0.08	28.4%
Track-Specific Attack Strategy	0.45	-0.67	0.95	0.72	24.6%
Potential Growth Type	-0.72	-0.55	-0.83	-0.78	37.9%

4.3. Test and analysis of the role of disciplinary competitions

4.3.1. Descriptive statistics of variables

After confirming that the indicators have good reliability and validity, we can enter the subsequent research stage more smoothly. In the first step, through the descriptive analysis of the data of each dimension, we can comprehensively grasp the current situation of college students' participation in disciplinary competitions, as well as the basic situation of the improvement of their various abilities. This process is of great significance for a comprehensive understanding of the current performance of college students in disciplinary competitions and its impact on creativity.

In this study, the obtained data were entered into SPSS statistical software and these data were preliminarily analyzed, and the descriptive statistical results of learning and analyzing ability (A), creativity (B) and comprehensive practice ability (C) are shown in Table 8. Among the data of each index, the communication and expression ability among the comprehensive practical abilities achieved the maximum value of 30.657.

Table 8. Descriptive statistical analysis results (N=2847)

Variable	Mean	SE	Skewness	SE	Kurtosis	SE
A1	8.575	2.200	1.166	0.151	0.305	0.290
A2	11.153	2.769	1.036	0.151	0.022	0.290
B1	9.243	3.478	0.834	0.151	0.449	0.290
B2	7.865	1.832	0.812	0.151	0.484	0.290
C1	6.444	1.808	0.982	0.151	0.052	0.290
C2	24.511	6.899	1.351	0.151	1.873	0.290
C3	30.657	5.825	1.731	0.151	1.786	0.290

4.3.2. Correlation analysis

The analysis of the correlation between two or more variables is called correlation analysis. It is usually used to analyze the consistency of trends in two or more sets of data. It is described by the correlation coefficient r. The range of values of r is [-1,1]. The judgment criteria of positive and negative relationship: if positive correlation, r>0; if negative correlation, r<0. The judgment of relationship strength: |r|>0.95 means strong correlation; |r|≥0.8 means high correlation; 0.5≤|r|<0.8 means medium correlation; 0.3≤|r|<0.5 means low correlation; |r|<0.3 means weak correlation.

The results of the correlation analysis are shown in Figure 2, where F1-F4 represent the results of four types of clustering, namely, comprehensive leadership, teamwork, track-specific excellence and potential growth. It can be seen that the correlation coefficient between the communication and expression ability (C3) in comprehensive practical ability and the potential growth type characteristics is the largest at 0.711, and the correlation coefficient between the ability indicators and the ability characteristics is between 0.305-0.711, all of which are moderately correlated.

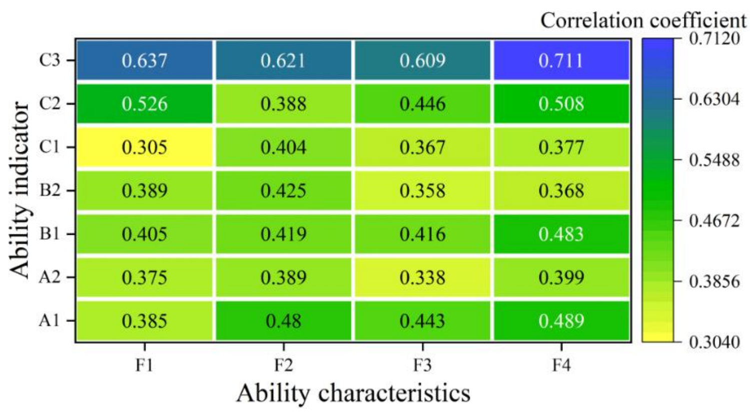

Figure 2. Results of Correlation Analysis

4.3.3. Tests for direct impact effects

Correlation analysis is designed to test whether there is a correlation between the variables and to measure the degree of correlation, correlation is not the same as determining the causal relationship, in order to clarify the causal relationship between the variables need to resort to regression analysis. Regression analysis is a statistical analysis method to study the causal relationship between two or more variables.

(1) Examination of the direct effect of academic competitions on learning analytical ability

First of all, the results of the model exploring the direct influence effect of academic competitions on learning analysis ability consisting of two dimensions: knowledge acquisition ability (A1) and problem finding ability (A2) are shown in Table 9. In the model, the regression coefficient value β of discipline competitions on the knowledge acquisition ability and the ability to find problems in learning analytic ability are 0.238*** (P<0.001) and 0.351** (P<0.005) respectively, which indicates that discipline competitions have a significant positive impact on learning analytic ability.

Table 9. The Impact of Subject Competitions on Learning Analytical Ability

Regression equation		**Overall fitting index**			**Regression coefficient**		
Predictor variable	Result variable	R	R2	F	β	t	p
Subject competition		0.734	0.535	48.382			
	A1				0.283	4.452	0.000***
	A2				0.351	7.038	0.004**

(2) Test of the direct effect of academic competitions on the evaluation of innovative ability

The results of the model of the direct effect of academic competitions on the evaluation of innovative ability consisting of two dimensions: problem identification ability (B1) and innovative thinking ability (B2) are shown in Table 10. The regression coefficient values β of academic competitions on problem identification ability and innovative thinking ability are 0.196*** (P<0.001) and 0.305*** (P<0.001) respectively, which indicates that academic competitions have a significant positive impact on evaluating innovative ability.

Table 10. The Impact of Subject Competitions on the Evaluation of Innovation Ability

Regression equation		**Overall fitting index**			**Regression coefficient**		
Predictor variable	Result variable	R	R2	F	β	t	p
Subject competition		0.809	0.652	75.784			
	B1				0.196	4.483	0.000***
	B2				0.305	7.741	0.000***

(3) Test of the direct effect of academic competitions on comprehensive practical ability

The model results of the direct influence effect of academic competitions on comprehensive practical ability consisting of three dimensions: problem solving ability (C1), teamwork ability (C2) and communication and expression ability (C3) are shown in Table 11. It can be found that the regression coefficient values of disciplinary competitions on problem solving ability, teamwork ability and communication and expression ability β are 0.225, 0.263 and 0.303, respectively, with P-values of less than 0.001, which indicates that the disciplinary competitions have a significant positive impact on the comprehensive practice ability.

Table 11. The Impact of Subject Competitions on Comprehensive Practical Ability

Regression equation		**Overall fitting index**			**Regression coefficient**		
Predictor variable	Result variable	R	R2	F	β	t	p
Subject competition		0.758	0.637	79.785			
	C1				0.225	4.437	0.000***
	C2				0.263	7.089	0.000***
	C3				0.303	5.225	0.000***

4.4. Educational Implications

Through multimodal data collection and modeling, the Competition Competency Framework deconstructs students' competition literacy into a quantifiable seven-dimensional competency framework, which provides a technical foundation for the transition from experience-driven to evidence-based decision-making in university competition education. By examining the three dimensions of education management, teaching implementation and student development, the framework helps to establish a closed-loop competition education system characterized by “data diagnosis-accurate intervention-autonomous development”. It realizes the upgrading from “experience selection” to “data-driven, accurate selection”, and thus promotes the reconstruction of the governance paradigm, guidance strategy and growth path of university competitions. In the empirical study of the impact of academic competitions on the development of college students' creativity, a series of hypotheses are verified through the comprehensive use of quantitative analysis methods, revealing the complex relationship between participation in academic competitions and the development of creativity.

In the context of building a strong education country and a strong talent country, discipline competitions have become a powerful engine for colleges and universities to cultivate students' innovative and practical abilities. This paper analyzes and summarizes the system of factors influencing college students' participation in discipline competitions, and constructs a seven-dimensional ability model. It is found that the influence and gold content of the competition have the greatest influence on college students' participation in academic competitions, which has a key influence on college students' participation in academic competitions both in terms of the degree of cause and root causes. In addition, the degree of attention and publicity given to competitions by colleges and the degree of perfection of competition incentives are also more root factors and have a higher degree of centrality, so these two factors are also easy to have an impact on the superficial factors. Based on the above conclusions, in order to improve the enthusiasm of college students to participate in disciplinary competitions and enhance the effectiveness of disciplinary competitions in educating people, this paper puts forward the following suggestions:

(1) Optimize the catalog of competitions and enhance the recognition of competitions

The influence and content of competitions are the most fundamental factors affecting college students' participation in disciplinary competitions. Therefore, a standardized catalog of disciplinary competitions should be formulated to enhance the influence and recognition of the competitions, and to stimulate the enthusiasm of colleges, instructors and students to participate in the competitions. Colleges should take the National Catalogue of Competitions for College Students in Ordinary Colleges and Universities as the basis, combine with the talent cultivation program and professional characteristics, formulate the classification catalog of disciplinary competitions in line with their own needs of school running, and update the catalog of competitions in a timely manner.

(2) Changing the concept of education and raising the importance of competitions

Colleges should establish the educational concept of "promoting learning and utilization by competition", take disciplinary competitions as an effective carrier of talent cultivation and an important hand for practical training, and pay attention to the cultivation of college students' ability of disciplinary competitions. First of all, the competition ability into the program. Integrate the cultivation of competition ability into the talent cultivation program, in order to increase the rigidity of the system, we can consider participating in at least one discipline competition during the university period as a condition for graduation. At the same time, students' participation in disciplinary competitions can be incorporated into the second classroom training program, and students' participation and awards can be transformed into second classroom hours and grades. Second, the competition ability into the curriculum. Courses are responsible for the cultivation of specific competition ability. For this reason, it is necessary to further integrate the cultivation of competition ability into the curriculum system, and clarify the status and role of different courses in the cultivation of competition ability. Finally, in order to facilitate the management, we can also consider the formation of virtual classes based on the competition projects, and the same competition project will be supervised by the professional instructor as the class teacher, and centralized and unified guidance.

(3) Improve the incentive mechanism to stimulate the motivation to participate in the competition.

The perfect degree of competition incentives is another fundamental factor affecting college students' participation in disciplinary competitions. For colleges, the following three aspects of incentives should be done: first, do a good job of incentives for students, in addition to material incentives, competition awards can be linked to credit hours and credits, assessment of awards and merits, thesis substitution, job recommendation, graduate school and other projects, multi-dimensional incentives; second, do a good job of incentives for instructors. Points model can be used, through the guidance of disciplinary competitions to obtain the corresponding competition points, and then the competition points into the evaluation of titles, workload assessment and other evaluation indicators, the formation of positive incentives feedback; third is to do a good job on the incentives for the professional teaching and research departments, organized competition guidance can achieve complementary advantages to improve the effectiveness of the guidance, for this reason, you can take the student participation in the results of the selection of excellent teaching and research department, excellent director of the teaching and research department Important indicators, and reward the teaching and research departments according to the award. The systematic competition incentive mechanism can constantly stimulate the motivation of students to participate in disciplinary competitions and teachers to guide disciplinary competitions.

5. Conclusion

The study mainly obtained the following conclusions:

(1) The subject competition competency portrait developed in this study embodies three major values of competition-based educational practice. The first is its concrete representation value, which visualizes abstract competencies through competency radar charts and heat maps of competition factors. Second is its reference and guidance value, the four competency development models derived from the

clustering results provide a framework for categorized teaching guidance. The last is its dynamic tracking value, which can capture the trajectory of students' ability development through the real-time monitoring function.

(2) Discipline competitions are an important way to improve students' innovation ability. Students strengthen the learning of innovative and entrepreneurial knowledge and professional knowledge through discipline competitions, and practice through competition projects, cultivating innovative ability, innovative thinking and innovative consciousness.

(3) This innovative talent cultivation mode can give full play to the initiative of instructors, students and student teams, and improve teamwork ability and innovation ability; through disciplinary competitions, students can improve their competition ability and personal comprehensive quality; through the construction of course content, competition management and other links, it improves the participation of instructors in the competition, and ultimately improves the effect of competition training and competition results.

In summary, this innovative talent training model is feasible, replicable and scientific, and it has certain reference significance for colleges and universities to cultivate innovative talents through disciplinary competitions.

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