

Research on Classification Method of Undergraduates' Creative Ability for Classified Teaching

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Abstract

In this paper, a quantitative system of undergraduates' creative ability is proposed through analyzing characteristics of Amabile creative theory, and the objectivity and feasibility of CAT, TTCT and AMS in creative ability quantification. The academic test scores, TTCT scores and AMS scores are used as the quantitative index of professional skills, innovation skills and task motivation in the quantitative system of undergraduates' creative ability. Classification method of undergraduates' creative ability using distance based K-medoids clustering method is proposed based on the quantitative system to improve the pertinence of creative ability cultivation. The feasibility and effectiveness of proposed classification method are verified by instance verification and effect analysis.

Keywords: higher education, classified teaching, classification of creative ability, K-medoids clustering

1. Introduction

It is an important task of contemporary higher education to cultivate comprehensive high-quality talents with innovation ability as the core feature (Mills, Pajares, & Herron, 2007), (Xu & Chen, 2010). At present, undergraduate teaching generally adopts the form of class teaching organization. Although it can quickly popularize scientific knowledge to meet the needs of large-scale cultivation of talents in large-scale industrial production, unified teaching methods and lesson preparation content often fail to fully cultivate the innovative ability of undergraduates with different professional foundations and personality abilities (Gunasekara, 2006). Classified teaching emphasizes adapting to the individual differences of students, focusing on the better development of all kinds of students on the basis of their own learning conditions, psychological characteristics and cognitive level, and strengthening the teaching guidance for different types of students purposefully (Jonassen & Grabowski, 2012), (Larson, 2000), (Bawarshi & Reiff, 2010). Therefore, classification teaching has become an effective way to solve the problem of insufficient teaching individualization and enhance students' innovative ability. Reliable student classification method is the basis of classified teaching, and the existing classified teaching practice mostly aims at enriching professional skills and improving the employing proportion (Charters & Good, 1945), so it mostly divides the students into single levels according to the degree of their knowledge mastery, or divides training orientation in generalities according to different employment intentions, few classified teaching practices have been carried out to quantify and classify students' innovative ability reasonably and meticulously (Brew & Mantai, 2017), (Felder & Brent, 2005), (Linnenbrink-Garcia et al., 2018). Therefore, students' innovative ability division method for classification teaching becomes the key to optimize the distribution of educational resources and improve the training effect of students' innovative ability. Aiming at the problem that there is no division method of students' innovative ability which can be directly used in classified teaching at present, by studying the evaluation technology and cluster analysis method of innovation ability, selecting objective evaluation index of innovation ability and effective density clustering algorithm, this paper puts forward a classification method of students' innovation ability for classified teaching, in order to provide theoretical basis and technical support for exploring the training mode of innovation ability.

2. Technical Analysis of Innovation Ability Evaluation

2.1 Amabile Sympathy Assessment Technology

Amabile believes that in all areas of expertise, innovation is the result of a combination of domain skills, innovation skills and mission motivation (Amabile, 1983). Among them, domain skills include basic knowledge in the professional field (principles, rules, examples, aesthetic standards, etc.), basic skills (experimental skills, operational skills, etc.) that should be mastered in the professional field, and other special talents required in the professional field; innovative skills Refers to the relevant techniques in the innovation activities and innovation process and the skills and methods to solve the problems, including cognitive style (the ability to break the mindset, flexible information classification skills, etc.), work style (focus ability, constructive forgetting ability) Etc., inspiring knowledge (any principle and method that helps to reduce the average difficulty of the problem), sensitivity to new things; task motivation refers to the individual's basic attitude toward the task and his or her cognition of the reasons for the task.

The Consensus Assessment Technique (CAT) proposed by Amabile based on the theoretical model of innovation capability relies on innovative products (Amabile, Conti, Coon, Lazenby, & Herron, 1996). The main evaluation ideas are as follows: First, the design tasks are required to complete the test; then, please Experts independently judge the innovation of products; finally, the comprehensive calculation experts confirm the consistency of product creativity, and the average value of expert scores is used as an indicator of product creativity.

Amabile's theory of innovation capability clarifies the sufficient and necessary components of innovation in all areas (Hocevar, 1981), and has an extremely important guiding role in the evaluation of innovation capabilities in the professional field. However, Amabile's CAT technology requires judges to have a consistent understanding of the ability to innovate, that is, CAT is based on a consistent implicit assumption (implicit view: an intrinsic belief that people use to interpret events in the environment, Make judgments and plan your own actions) (Guilford, 1966). In the actual operation process, it is more difficult to satisfy the assumption that the implicit view is consistent. In addition, CAT has high requirements for the task of initiating creative products or reactions, and a single product is not easy for the judge to reasonably evaluate the subject skills of the subjects (Guilford, 2006). Therefore, it is necessary to find more objective evaluation criteria based on Amabile's theoretical framework of innovation capability to ensure the objectivity and feasibility of the method of dividing students' innovative ability.

2.2 Torrance Innovation Thinking Test

The Torrance Tests of Creative Thinking (TTCT) is currently the most widely used method of innovation capability evaluation (Karwowski, 2008), (Dyson et al., 2016), (Said-Metwaly, Fernández-Castilla, Kyndt, & Van den Noortgate, 2018). Torrance defines innovation capability as a process: innovation capability starts with a keen awareness of existing problems; identifies the causes of problems; seeks ways and means to solve problems; makes assumptions about problem solving; iteratively tests and modifies Assumptions; finally draw conclusions and inform others of the results (Heausler & Thompson, 1988).

The TTCT consists of 12 sub-tests, divided into 3 sets, which range from kindergarten to adult (Sternberg, 1999), (Kim, 2011), (Wechsler et al., 2018). The first set of tests is a verbal creative thinking test that includes seven sub-tests, which are scored according to the fluency, flexibility, and originality of the expression or expression. The second set of tests is a picture-innovative thinking test that consists of three sub-tests, which are based on basic pattern plots and scored for fluency, flexibility, originality and precision. The third set is an innovative thinking test of sound words, including two sub-tests. The sub-tests are verbal responses, freely imagine the stimulus, and write about the related objects or activities, and according to the rareness and uniqueness of the reaction.

TTCT is based on norm reference, which is easy to use, universal in application and high in reliability. However, it can be seen from the test content of TTCT that it mainly completes the evaluation of the innovative thinking by quantifying the expression of the routine form of the subject. In the process of cultivating students' innovative ability, we should focus on cultivating the innovation ability in the professional field to achieve the purpose of learning and using it. Therefore, it will not meet the innovation ability in the student field only using TTCT score as the index of innovation ability.

2.3 Selection of Innovation Ability Test Indicators

Comprehensive analysis of Amabile's innovation capability theory, CAT and TTCT shows that TTCT has no requirement for the consistency of implicitness, so it has higher operability and reliability than CAT. However, TTCT focuses on the evaluation of cognitive styles, inspirational knowledge, etc., and only corresponds to the

innovative skill block of Amabile's innovative ability theory. In the process of cultivating students' innovative ability, it is convenient to implement the assessment of domain skill blocks in Amabile's innovative ability theory through the conventional methods of coursework examination. It has been revised, proved and widely adopted by domestic and foreign scholars. The Achievement Motivation Scale (AMS) has stable structural factors and good reliability and validity. It can be applied to the task motivation block of Amabile's innovative ability theory.

Therefore, this paper takes Amabile's innovation ability theory as the evaluation framework, takes the academic test scores as the indicators to quantify the student field skills, uses the TTCT score as the index of quantitative innovation skills, and uses the AMS score as the indicator of the quantitative task motivation.

3. Analysis of Clustering Methods for Classification Teaching

Clustering analysis is an important data mining method. According to different clustering criteria, the data objects are grouped through unsupervised learning process. The clustering analysis finally generates cluster clusters, so that the objects in the cluster are as similar as possible, and the data objects between the clusters are as different as possible (Abbasi & Younis, 2007), (Nayak, Naik, Kanungo, & Behera, 2018), (Esnashari, Gardner, & Watters, 2018). According to different clustering criteria, clustering analysis methods can be divided into Partitioning Method, Hierarchical Method, Grid-based Method, and Model-based Aggregation, Model-based methods, Density-based Method, etc. (Ienco, & Bordogna, 2018).

3.1 Division Clustering Method

The basic idea of the partitioning clustering method is to select the initial center point, determine the initial cluster partitioning, and repeatedly reduce the error value of the objective function by the iterative operation, and gradually reduce the error value of the objective function, and finally divide the data into multiple clusters. The K-means algorithm and the K-medoids algorithm belong to the classical partitioning clustering method, which has the advantages of high execution efficiency and simple implementation. However, the partitioning clustering takes the minimum distance to the cluster center as the iterative target. The uniqueness of the clustering center makes the partitioning clustering method easy to solve the problem of boundary segmentation when dealing with non-spherical cluster data.

It can be seen from Figure 1 that, due to the non-spherical clusters of data, the boundaries of the three data clusters in the partitioning result are relatively regular, and the partitioning results are quite different from the intuitive cognition, but the distance from the data to the center of the cluster is within a certain range. Therefore, if the teaching plan is formulated according to the cluster center, the radiation range of the teaching effect will be consistent with the clustering result.

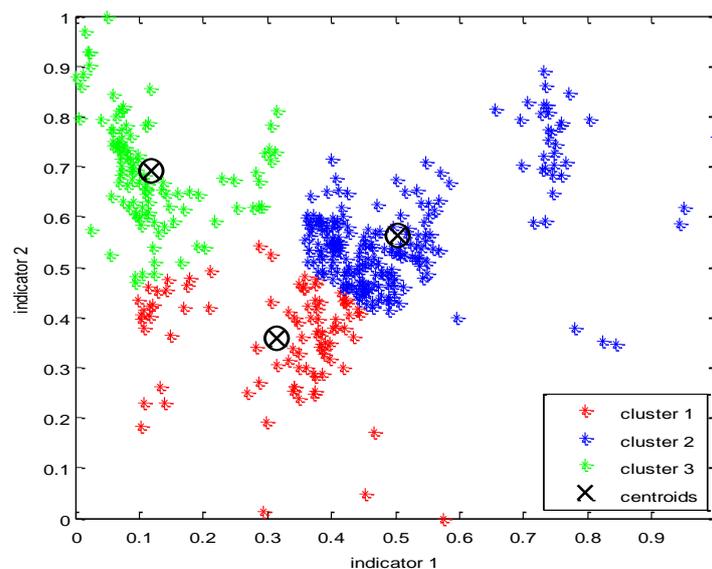


Figure 1. Example of dividing clustering results (K-medoids clustering algorithm)

3.2 Hierarchical Clustering and Grid Clustering Method

The hierarchical clustering method classifies all data objects into one cluster or divides each data object into a single cluster, and then iterative splits or merges the original clusters until the termination condition is reached.

The iterative steps of the hierarchical clustering method and the partitioning clustering method are different, but the evaluation indexes of the iterative are all distances, so the characteristics of the clustering results are not much different.

The grid-based clustering method divides the data space into a grid structure of finite cells, and clusters the cells as the basic unit. The evaluation indexes of the iterations are also distances. The grid-based clustering method has a faster processing speed, but the speed is improved at the expense of the partitioning precision. The grid-based clustering method has relatively different clustering edges, which is quite different from the intuitive cognition.

3.3 Model Clustering Method

Model-based clustering methods are often based on the assumption that data has a potential probability distribution law. It defines the data with similar features as the same cluster by discovering and describing each data. Since the model-based clustering method mostly uses the maximum expectation algorithm, then iteratively calculates the posterior density function, and then obtain the model parameters, it has the characteristics of simple and stable, but it is easy to fall into the local optimum (Nanda, &Panda, 2016).

It can be seen from Fig. 2 that, due to local optimum, data cluster 1 and data cluster 2 have similar cluster centers. If the teaching scheme is formulated according to the cluster center, the radiation range of the data cluster 2 teaching effect will be significantly different from the clustering result.

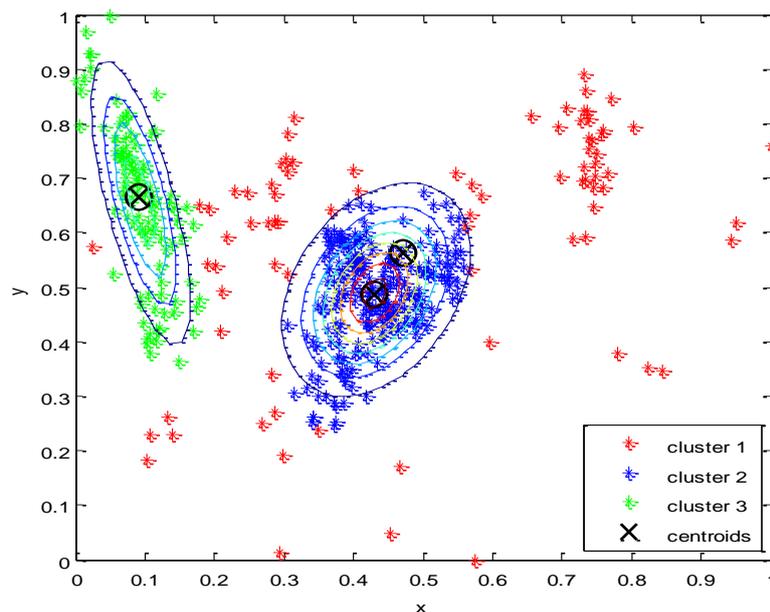


Figure 2. Example of model clustering results (hybrid Gaussian model algorithm)

The density clustering method treats clusters as high-density object regions separated by low-density regions. Its main idea is that for a data object in data centralization, it is required to contain at least a given number of points within a given radius. The advantage of the density clustering method is that clusters of arbitrary shapes can be found, the clustering speed is fast, and the noise data can be effectively filtered.

It can be seen from Fig. 3 that the edges of the data clusters 1, 2, and 3 are consistent with the data distribution, and the boundary is not hard, and the discrete points with larger spacing are divided into the same data cluster, which is in line with the visual cognition. However, the density clustering method has no clear clustering center, and there are students in the discrete data cluster 4 suitable for the teaching scheme of data cluster 1 and data cluster 2. Therefore, the density clustering method is not suitable for classification teaching division.

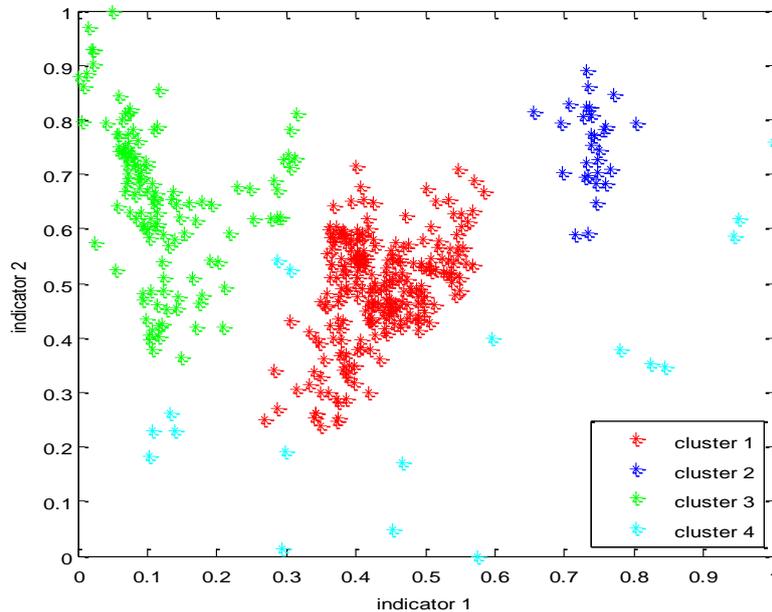


Figure 3. Example of density clustering results (DBSCAN algorithm)

4. Student Innovation Ability Division Method and Case Analysis

4.1 Student Innovation Ability Division Method

After comprehensive analysis of different innovation ability evaluation techniques and cluster analysis methods, this paper takes the academic achievement, TTCT score and AMS score as the evaluation indicators of domain skills, innovative skills and task motivation. According to the actual situation of teaching staff and teaching resources, determine the number of divisions. K-medoids clustering method which is not sensitive to noise and suitable for small data clustering is selected. The number of divisions is taken as the value of K-medoids clustering parameter K, so that the innovation index data is divided, and then the teaching is based on the data cluster center. Cultivate programs to develop and improve the innovation ability of all types of students. The division method flow is shown in Figure 4.

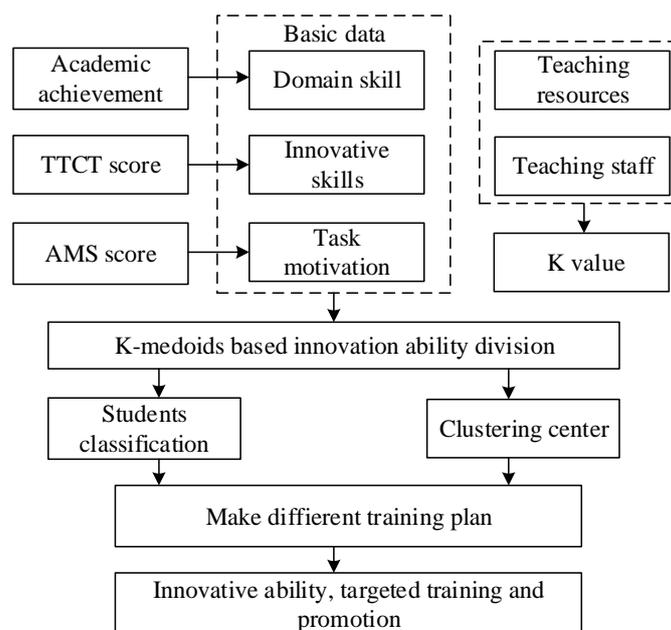


Figure 4. Process of innovation capability division method

The specific implementation steps are as follows:

- (1) Conducting the course test, TTCT test, and AMS test for the students, and taking the academic achievement score, TTCT score, and AMS score as the domain skill data, innovation skill data, and task motivation data required for the innovation ability division.
- (2) According to the teaching resources and teaching conditions, the number of classification categories is determined, and the number of division categories is taken as the value of the parameter K in the K-medoids cluster.
- (3) Using the K-medoids clustering method to cluster the innovation ability data.
- (4) According to the K-medoids clustering results, the students in the same data cluster are divided into the same innovation ability class, and according to the location of the cluster center, different innovation ability training programs are formulated to specifically improve the innovation ability of students with different innovation ability.

4.2 Examples of Innovation Capability Division

The 256 undergraduate course test scores of a college 2015 were collected, the TTCT test was performed and the test score T was recorded, the AMS test was performed and the achievement motivation score M_s and the fear failure score M_f were recorded, and the achievement tendency score M ($M = M_s - M_a$) was taken as the AMS final score. The scores of 256 undergraduate innovation ability tests are shown in Figure 5.

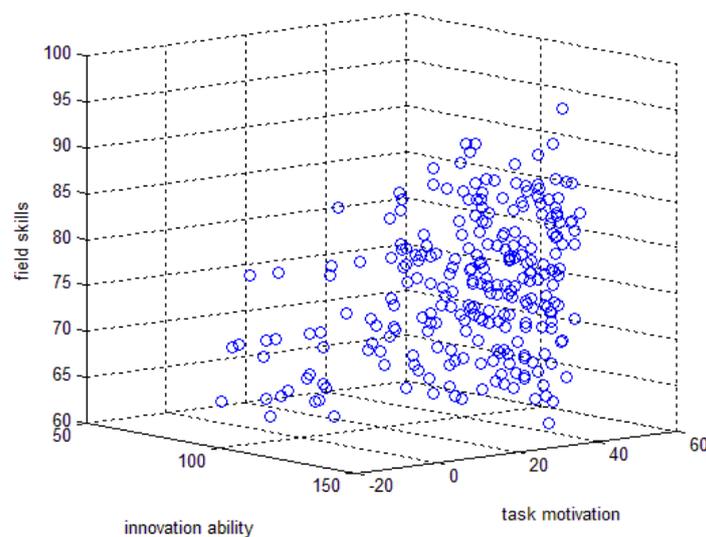
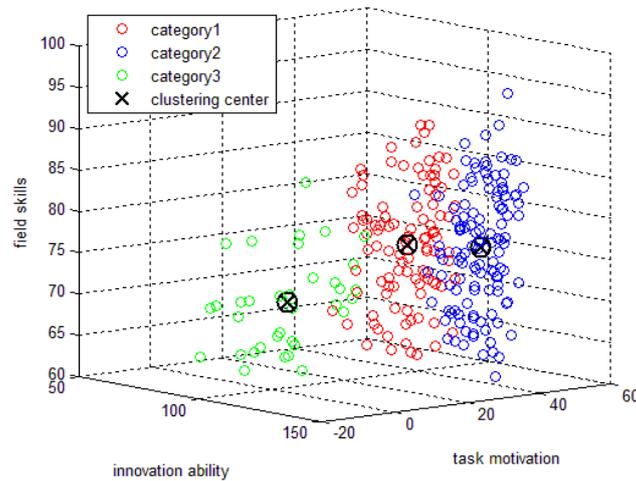


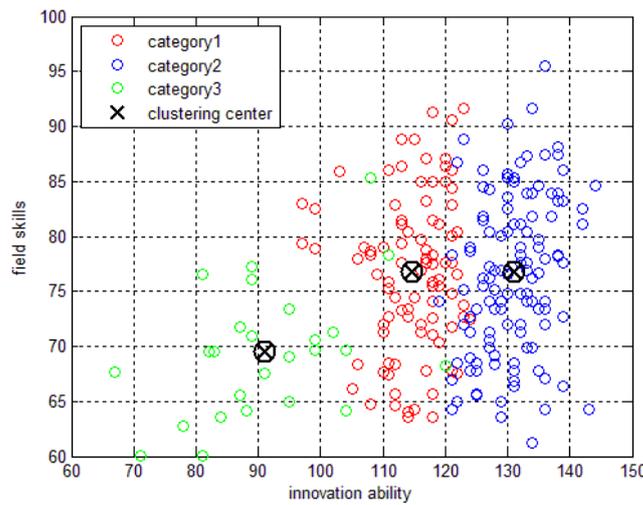
Figure 5. Innovation ability test score

- 1) First, use the method proposed in this paper to divide the innovation ability.

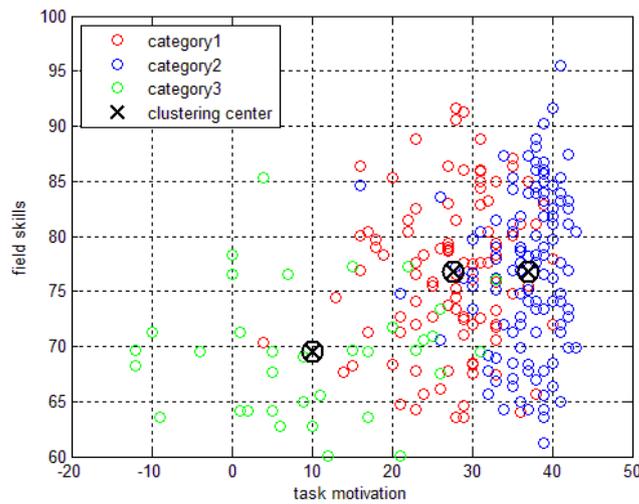
According to the teaching conditions of teaching resources and teaching staff, the number of classification categories is determined to be 3, and the value of parameter K in the K-medoids cluster is set to 3. The K-medoids clustering method is used to perform three-dimensional clustering of innovation capability data. The three-dimensional clustering results of K-medoids are shown in Fig. 6.



a) 3D view of the results



b) Innovative skills to segment results - domain skills view



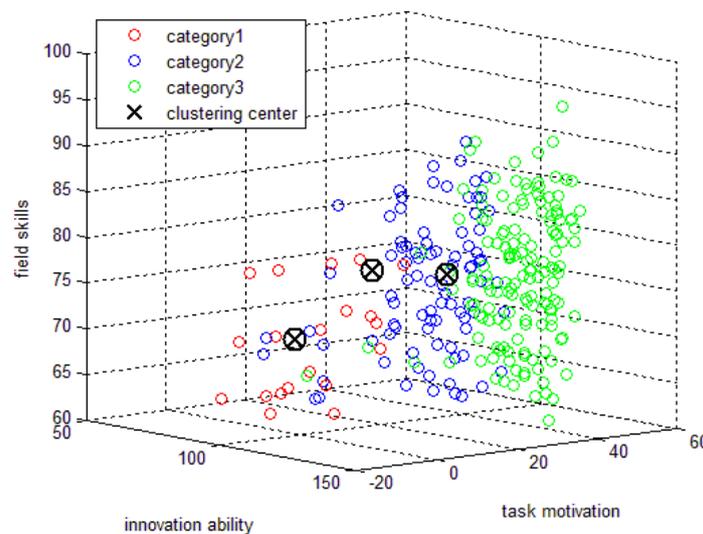
c) Task motivation to segment results - domain skills view

Figure 6. Results of the innovative ability of the method in this paper

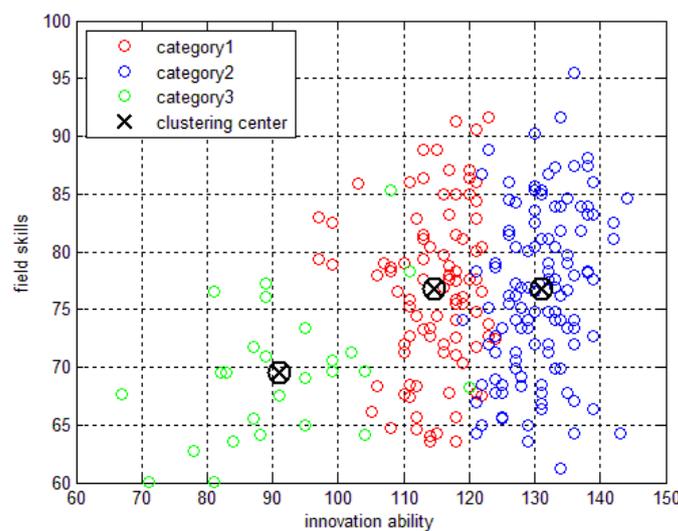
K-medoids clustering results shows that the cluster center of category 1 has lower field skills, innovative skills, and task motivation. Therefore, when setting up innovative ability training programs, the basic skills should be consolidated. Teaching innovative methods and cultivating innovative motivations as the focus of teaching; category 2 cluster centers correspond to domain skills in three categories, while innovation skills and task motivation are in the middle, so when setting up innovative capacity training programs, On the basis of ensuring high-level domain skills, training innovative skills and stimulating innovation motivation as the focus of teaching; Category 3 cluster centers have higher corresponding domain skills, innovative skills, and task motivations. It is necessary to expand the field of vision of the professional field, improve the level of innovative skills, and increase the opportunities for innovation and practice as the focus of teaching.

2) In order to compare the differences between the proposed method and the traditional method of division, the division of innovative methods is taken as an example to divide the single index equalization method.

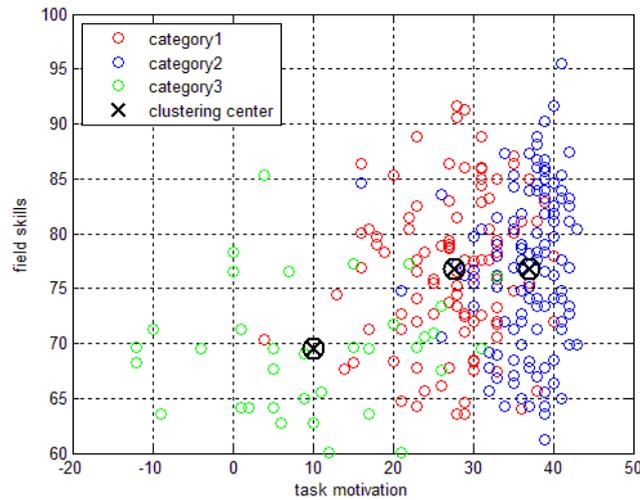
According to the teaching resources and teaching conditions, the number of classification categories is determined to be 3, and the innovation skill intervals are divided into 3 sub-intervals. The results based on the division of innovation skills are shown in Figure 7.



a) 3D view of the results



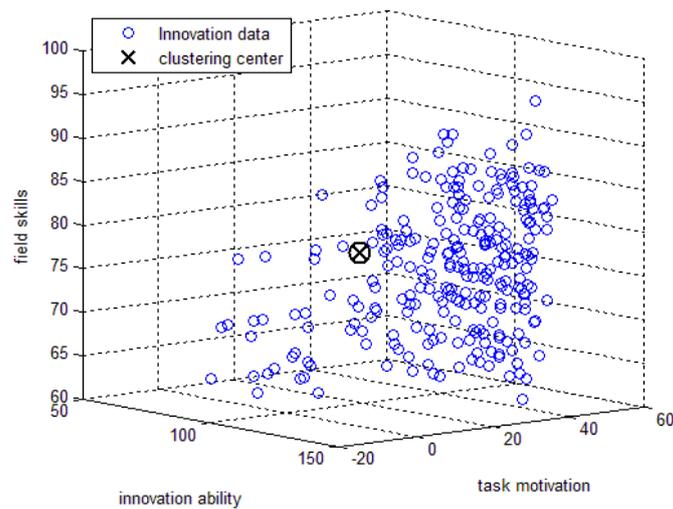
b) Innovative skills to segment results - domain skills view



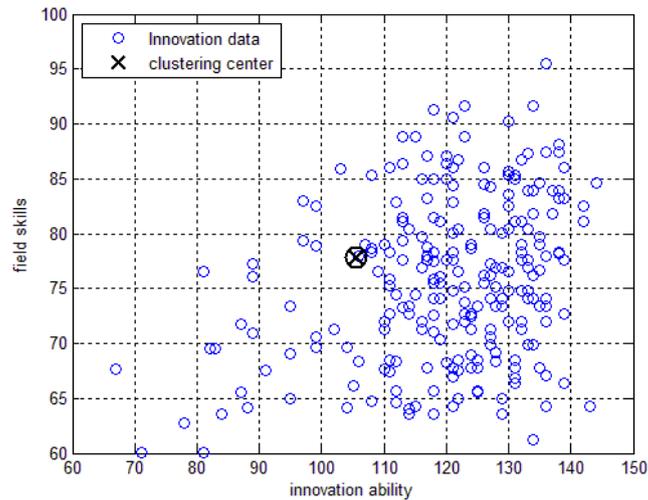
c) Task motivation to segment results - domain skills view

Figure 7. Innovative skills based on the division of innovation capabilities

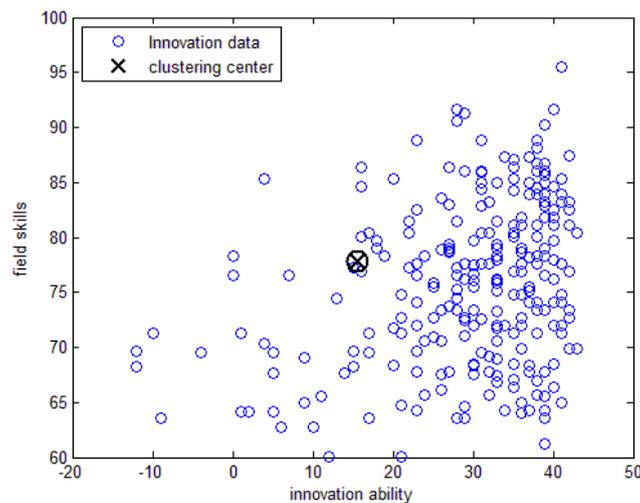
3) To further compare the differences between the proposed method and the traditional partitioning method, the data center of the innovation capability without division is determined. The data center location is shown in Figure 8.



a) 3D view of the results



b) Innovative skills to segment results - domain skills view



c) Task motivation to segment results - domain skills view

Figure 8. Undivided Innovation Capability Data Center

4.3 Analysis of the Effect of Innovation Ability Division

1) Analysis of innovation capability assessment framework and quantitative indicators

Taking Amabile's theory of innovation ability as the evaluation framework, using the three quantifiable indicators of academic achievement, TTCT score and AMS score to refine the innovation ability, it is more conducive to field skills, innovative skills and tasks than the conventional single innovation ability evaluation method. Motivation analyzes and classifies innovation ability from three different perspectives, which can provide a basis for the targeted cultivation of innovation ability.

2) Analysis of the classification effect of innovation ability and development plan

In order to quantify the partitioning ability division effect, the K-medoids, the equalization method, and the non-divided three methods are used to extract the Euclidean distance cumulative values from the data points of each category to the category center to characterize the distance from the data point to the category center.

Table 1. Euclidean distance of different division methods

division method	category1	category2	category3	sum
K-medoids	571.41	1048.95	1113.02	2733.38
Equalization method	260.71	1528.43	3338.22	5127.36
No treatment	-	-	-	6799.10

Using K-medoids clustering method to classify innovation ability, not only can directly obtain the cluster center representing the category characteristics, as can be seen from Table 1, the K-medoids clustering method can be used to effectively reduce the data points to categories. The Euclidean distance of the center narrows the distribution range of various students' relative teaching goals, and makes the innovation ability training program based on the spatial position of the cluster center more targeted, and thus effectively improves the innovation ability for various student characteristics.

5. Conclusion

Through the results of the innovation ability division, Amabile's innovative ability theory is used as the evaluation framework. The academic test scores are used as indicators to quantify the student field skills. The TTCT score is used as an indicator to quantify the students' innovative skills, and the AMS score is used as an indicator to quantify the motivation of the student tasks. It is feasible to quantify the students' ability to innovate and provide basic data for the division of innovation capabilities.

Compared with the conventional partitioning method, the distance-based K-medoids clustering method can more effectively divide the students' innovative ability in three dimensions, and the Euclidean distance from each category of data points to the category center is small, which can improve the innovation ability targeted. And the cluster centers that are divided can represent various characteristics, which can be used as a basis for guiding the development of targeted training programs, thereby reducing the difficulty of cultivating targeted innovation capabilities.

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