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Analysis of Challenges and Opportunities of Innovation and Entrepreneurship Education for College Students in the Digital Era

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SUMMARY: *Innovation and entrepreneurship education is the key pivot for the in-depth implementation of "mass entrepreneurship and innovation". The study goes beyond the single causal factor of innovation and entrepreneurship quality improvement, and introduces the fuzzy set qualitative comparative analysis (fsQCA) method, based on the questionnaires of 524 college students, to examine the combination paths of six dimensions: theoretical teaching, faculty allocation, practical activities, service platform, incentive policies and cultural atmosphere from a group perspective. The innovation and entrepreneurship education data are further utilized to portray individual student characteristics. Seventeen multi-dimensional behavioral data including online/offline learning, innovation practice, and output are obtained, and a fine-grained learner profile is constructed, and a deep belief network (DBN) model is constructed to realize the recommendation of innovation and entrepreneurship education curriculum resources. The study reveals five combination paths of "high faculty-practice-driven", paths and "teaching-motivation-practice-driven" that lead to high activity in creative industries, with a consistency of 0.869. Based on students' final grades and extracurricular practical activity scores, the study clustered five groups, namely, Overall Leaders (78), Academically Focused (146), Balanced Developers (169), Practice-Oriented (63), and Lagging Developers (69), to provide the coordinates for accurate profiling and interventions.The DBN achieved F1=0.34% and 95.19% for both student profile similarity matching and course prediction and recommendation. 91.34% and 95.19% excellent results.*

KEYWORDS: *innovation and entrepreneurship education; fsQCA; cohort analysis; learner portrait; deep confidence network; resource recommendation*

1 Introduction

Innovation and entrepreneurship education is an important part of college education, which can not only improve students' innovation and entrepreneurship ability, but also promote the overall development of students [1, 2]. In the context of digitalization, the impact of digital technology has brought many challenges to college students' innovation and entrepreneurship education. The first is the lack of digital talents, the rapid development of digital technology, colleges and universities in a fixed period of time can not quickly cultivate teachers with digital ability and innovation and entrepreneurship education ability, so that the innovation and entrepreneurship education in colleges and universities can not keep pace with the times in a timely manner [3-6]. Secondly, the innovation and entrepreneurship education market competition is fierce, under the digital era, major universities have carried out innovation and entrepreneurship education,

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and a large number of excellent entrepreneurial students and entrepreneurial projects have emerged [7, 8]. College students' innovation and entrepreneurship face the double challenge from competitors in the same industry and cross-industry competitors, and need to have a stronger sense of competition and competitiveness [9, 10].

Of course, the digital era also brings new development opportunities for college students' innovation and entrepreneurship education, which is manifested in technological progress, information sharing and entrepreneurship policy support [11, 12]. The continuous emergence of emerging technologies, such as the Internet, artificial intelligence, big data, etc., provides possibilities for enriching innovation and entrepreneurship education [13, 14]. Through the use of advanced technology, it helps innovation and entrepreneurship education break the traditional teaching barriers, develop new business models, and promote the development of teaching quality [15, 16]. At the same time, information sharing is more convenient and efficient, and the latest information and market dynamics of various industries can be obtained through the Internet, which reduces the cost of information acquisition and improves the efficiency of innovation and entrepreneurship education [17, 18]. And in order to promote the development of college students' entrepreneurship education, governments at all levels have introduced a series of supportive policies, including entrepreneurship subsidies, tax incentives, business incubation base construction, etc., which provide policy guarantee and financial support for innovation and entrepreneurship education. The introduction of these policies has provided a more favorable external environment for innovation and entrepreneurship education [19-22].

Based on fsQCA, the study reveals the grouping patterns that lead to high activity in innovation and entrepreneurship education, and integrates the grouping paths into the recommendation of learner resources, which can be transformed into implementable educational programs. The study attributes the quality of innovation and entrepreneurship education to six variables, namely, theoretical teaching, faculty allocation, practical activities, service platform, incentive policies and cultural atmosphere, and identifies the high activity groupings among the antecedent conditions based on fuzzy set qualitative comparative analysis (fsQCA). Based on this, an online learning space model integrating resources, practice and community is proposed. The system includes underlying cloud computing, big data and other technical support to include functional modules such as course resources, virtual practice, display and sharing. Further design the educational data collection framework, including students' online and offline learning behaviors and innovation and entrepreneurship practices and achievements, to outline the learner portrait. Finally, we design a recommendation method based on course profiles and Deep Belief Network (DBN) to achieve accurate matching between massive resources and personalized needs. Through deep learning to understand student characteristics and course qualities, we recommend the most appropriate innovation and entrepreneurship learning resources for students.

2 fsQCA-based quality analysis of college students' innovation and entrepreneurship education

2.1 Fuzzy set-based qualitative comparative analysis method (fsQCA)

2.1.1 Logical algorithms followed by fuzzy sets

Fuzzy sets follow three basic logical algorithms, negation, logical sum and logical or. These three logical algorithms provide important background knowledge for understanding how to use fuzzy sets.

Negation. Like clear sets, fuzzy sets are subject to the law of negation. With a clear set, negation switches the affiliation score from 1.0 to 0.0, and from 0.0 to 1.0. For example, negating the clear set of democracies is a clear set of non-democracies. This simple mathematical principle also applies to fuzzy algebra, but the relevant values are not limited to the two Boolean values 0.0 and 1.0; they extend to values between 0.0 and 1.0. In order to compute the affiliation in the case of the negation of a fuzzy set M, one simply subtracts the members of the set M from 1.0, i.e., the affiliation of the set M negating the set $(\sim M)$ of the set $=1-M$ or the affiliation of the set $\sim M=1-M$

Logical sum. This algorithm comes into play when two or more sets are combined to form a composite set and is often referred to as the intersection of sets. For example, if a country has a poverty affiliation score of 0.6 and a democracy affiliation score of 0.4, then its poverty and democracy affiliation scores are taken to be the intersection of the two affiliation scores, i.e., the smallest of the two scores, 0.4. The combination of a set A and a set M is denoted by $A*M$, with * denoting the logical sum, i.e., the intersection of the two sets.

Logical or. Two or more sets can also be connected by a logical or, which usually refers to the union of sets. When using fuzzy sets, the logical or directs the researcher's attention to the maximum value of the affiliation score for each case in the combined set. For example, if a country has an affiliation score of 0.6 for poverty and 0.4 for democracy, then the affiliation score of whether it is poor or democratic is taken to be the concatenation of the two affiliation scores, i.e., the largest one, 0.6. The algebraic expression for a set A or a set M is $A+M$ where + is used to denote a logical or.

2.1.2 Steps of qualitative comparative analysis method based on fuzzy sets

(1) Identify cases and determine outcome variables and antecedent elements. First, the researcher collects relevant cases for the problem under study, identifies relevant cases that can illustrate the problem, and acquires knowledge of the relevant cases; second, based on the cases under study, identifies outcome variables that can explain or prove the problem; and lastly, identifies the main antecedent elements related to the outcome based on relevant theoretical knowledge and practical experience.

(2) Calibration data. After determining the antecedent elements and outcome variables, the data of the relevant variables of each case are calibrated, and the data are converted into fuzzy set data of 0~1. The researcher determines the standard of key fuzzy affiliation scores based on the relevant theoretical knowledge and the actual case situation, and calibrates the data through fsQCA software, and data calibration is a key step in using the fsQCA method.

(3) Construct the truth table. Multiple antecedents are combined in different ways to form different configurations, and the truth table categorizes each case according to different configurations, and all logically possible combinations are listed. Subsequently, the researcher filters the cases by setting consistency thresholds and frequency thresholds to remove cases and configurations that do not meet the conditions.

(4) Truth table analysis. fsQCA software will perform a standard analysis of the constructed truth table, and three different solutions will be obtained through simple class counterfactual analysis and difficult class counterfactual analysis: complex solution, concise solution, and optimized solution. Simple-type counterfactual analysis is used when the researcher is confident that there are redundant conditions incorporated into a particular antecedent configuration, and that whether or not the configuration leads to the interpreted outcome is independent of the redundant conditions, in which case the redundant conditions can be moved out of the configuration in order to simplify the combination of conditions. Difficult counterfactual analyses are those in which the researcher, in the absence of a clear theoretical

determination of whether a condition is redundant or not, and in which the available case data do not prove that the configuration after removal of the condition does not lead to the interpreted result, moves the condition out of the configuration for the sake of simplifying the configuration. The complex solution is the result without counterfactual analysis, the optimized solution is the result based only on the simple class of counterfactual analysis, and the parsimonious solution is the result after two classes of counterfactual analysis.

(5) Result Evaluation. The evaluation of the results of the truth table analysis includes two aspects, the first is to evaluate the adequacy and necessity of the configurations by analyzing the consistency and coverage results of each configuration, and to evaluate the mechanism and practical significance of the existence of the configurations. The second is to identify the cases in which each conformation fits, and to discover the important information implied in the cases through in-depth analysis of the cases.

2.1.3 Sufficiency and necessity of fuzzy sets

An important purpose of using qualitative comparative analysis is to assess the adequacy and necessity of the antecedent elements. Two important indicators are used to assess adequacy and necessity: consistency and coverage. The subset principle applies to fuzzy sets; a set A is said to be a subset of a set B if the subordination score of the set A is less than or equal to the subordination score of the set B. Sufficiency and necessity assessment is an application of the subset principle; in order to prove necessity, the researcher must show that the effect is a subset of the cause. And in order to support an argument for sufficiency, the researcher must show that the cause is a subset of the effect. Consistency measures the degree to which a given antecedent conditional configuration explains the causal outcome; that is, consistency indicates the degree to which a subset of relationships is approximately perfect. Coverage the degree to which the antecedent condition or antecedent conditional configuration empirically explains the outcome, i.e., coverage reflects empirical relevance and significance.

The formula for X being a sufficient condition for consistency of Y is as follows:

$$Consistency\left(X_i \le Y_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(X_i\right) \tag{1}$$

X is a necessary condition for the consistency of Y calculated as follows:

$$Consistency\left(Y_i \le X_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(Y_i\right) \tag{2}$$

Sufficiently conditioned coverage formula:

$$Coverage\left(X_1 \le Y_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(Y_i\right) \tag{3}$$

Coverage formula for necessary conditions:

$$Coverage\left(Y_i \le X_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(X_i\right) \tag{4}$$

2.2 Screening and treatment of factors influencing the quality of innovation and entrepreneurship education

2.2.1 Factors affecting the quality of innovation and entrepreneurship education in higher education institutions

The study divides the factors influencing the quality of innovation and entrepreneurship education in colleges and universities into six dimensions: theoretical teaching, faculty allocation, practical activities, service platform, incentive policies and cultural atmosphere, and each dimension contains 2-4 items under each dimension. The indicator of innovation and entrepreneurship activity is selected as the outcome variable of innovation and entrepreneurship education quality in colleges and universities, which contains 5 items. The variables of innovation and entrepreneurship education quality and influencing factors in colleges and universities constructed in this paper are shown in Table 1.

Table 1: Influence factors of the quality of Innovation and Entrepreneurship Education

	Dimension	Item
Causal variable	Theoretical Teaching	Professional courses are closely linked with practical experiences.
		Inclusive education content of general courses integrates elements of innovation and entrepreneurship.
		The theoretical teaching content of innovation and entrepreneurship education is diverse and rich.
		The teaching methods for innovation and entrepreneurship are flexible and diverse.
	Teacher Allocation	Teachers have certain practical experience in enterprises or entrepreneurship.
		The school hires outside entrepreneurs to serve as mentors for innovation and entrepreneurship.
	Practical Activities	The school frequently holds innovation and entrepreneurship competitions.
		The school provides students with opportunities for enterprise exchanges.
		The school organizes students to participate in innovation and entrepreneurship internships or practical training.
	Service Platform	The school has established a complete entrepreneurial practice platform.
		The school provides comprehensive entrepreneurial information and consultation services.
	Incentive Policies	The school rewards students for their innovation and entrepreneurship achievements.
		The school provides financial support for students' innovation and entrepreneurship practices.
	Cultural Atmosphere	The school's cultural atmosphere encourages students to actively participate in innovation and entrepreneurship.
		The campus frequently publicizes successful cases of teachers and students in innovation and entrepreneurship.
Result variable	Innovation and Entrepreneurship Activity	Take elective courses related to innovation and entrepreneurship.
		Participate in the college students' innovation and entrepreneurship training projects.
		Join entrepreneurship or technological innovation clubs.
		Have participated in entrepreneurship plan competitions.
		Actively pay attention to and utilize the entrepreneurial policies and resources provided by the school or the government.

2.2.2 Data sources and reliability analysis

Now, based on the theory of entrepreneurial ecosystem, the theory of entrepreneurial process, and with reference to mature studies such as Individual Entrepreneurial Intention Scale, Self-Efficacy Scale, and Student Participation, the Likert 5-point option is used to prepare the above four-dimensional scale form. Combining electronic and paper questionnaires, 38 colleges and universities that offer innovation and entrepreneurship education courses at the undergraduate level were selected as the research subjects. A total of 573 questionnaires were distributed online and offline, and after excluding invalid questionnaires, 524 valid questionnaires were recovered, with an effective recovery rate of 91.45%. Among the 524 college student samples surveyed, 68.89% (361/524) of the families supported students' self-entrepreneurial behaviors, 86.07% (451/524) of the family members had entrepreneurial experience, 12.98% (68/ 524) of college students have had entrepreneurial experience or are trying to start their own business.

Reliability analysis shows that the overall KMO value of the questionnaire is 0.921, and the factor loadings of each item are all greater than 0.7, indicating that the questionnaire has good structural validity and the items are highly correlated. The Cronbach's alpha coefficients for the dimensions of theoretical teaching, faculty allocation, practical activities and incentive policies were 0.928, 0.909, 0.938, 0.912, 0.915 and 0.934, respectively.The combined reliability CRs were 0.878, 0.912, 0.885, 0.869, 0.907 and 0.921, which are all greater than 0.850.The Cronbach's alpha coefficient of the outcome variable innovation and entrepreneurship activity and the combined reliability CR are 0.931 and 0.936 respectively.The overall internal consistency of the questionnaire is high and has good reliability. The average variance extracted values ((AVE) for each dimension are also greater than 0.5, indicating that the questionnaire has good convergent validity.

2.3 Group state analysis of innovation and entrepreneurship activity based on fsQCA

2.3.1 Necessary Condition Detection of Predecessor Variables

Based on the questionnaire results of 524 university students, 178 student samples are known to be highly innovative and entrepreneurially active, leaving 346 students as non-highly innovative and entrepreneurially active, and then based on the results of the antecedent variables of each student, statistics based on the fuzzy set qualitative comparative analysis are conducted.

The necessary condition to measure whether the antecedent variable is the outcome variable depends mainly on the consistency score of the variable with respect to the outcome. Consistency scores are analogous to coefficient significance in regression statistical analyses and characterize the extent to which the outcome needs to rely on the presence of the conditioning variable. When the consistency score is greater than 0.9, the variable is considered necessary for the outcome. The results of the consistency test of the antecedent variable on the outcome variable in this study are shown in Table 2.

Table 2: Consistency of the predictor variable with the outcome variable

	High IEA(N=178)		Non-high IEA(N=346)	
	Consistency	Coverage	Consistency	Coverage
Theoretical teaching	0.771	0.7634	0.561	0.574
~Theoretical teaching	0.566	0.56	0.784	0.775
Staff allocation	0.757	0.751	0.561	0.542
~Staff allocation	0.564	0.586	0.752	0.772
Practical activities	0.716	0.693	0.616	0.551
~Practical activities	0.538	0.579	0.699	0.743
Service platform	0.708	0.724	0.577	0.531
~Service platform	0.536	0.568	0.704	0.745
Incentive policies	0.776	0.737	0.633	0.591
~Incentive policies	0.631	0.607	0.685	0.741
Cultural atmosphere	0.686	0.702	0.585	0.542
~Cultural atmosphere	0.481	0.522	0.712	0.774

The consistency coefficients of the six antecedent variables of the quality of innovation and entrepreneurship education in colleges and universities range from 0.481 to 0.786, which does not reach the threshold value of 0.9, i.e., there is no single factor that constitutes a necessary condition for high innovation and entrepreneurship activity or non-high innovation and entrepreneurship activity. For “high innovation and entrepreneurship activity”, the consistency of practical activities, incentive policies and theoretical teaching is relatively high, respectively 0.786, 0.776 and 0.771, indicating that the three have more important roles in promoting activity, but still far from reaching the level of necessary conditions.

The effect of innovation and entrepreneurship education in colleges and universities is not dependent on one independent factor, but is the result of the synergistic effect of multiple factors combined with each other. In this regard, we turn to the group perspective to explore which combinations of factors can jointly lead to high innovation and entrepreneurship activity.

2.3.2 Configuration analysis

To avoid potential contradictory groupings, this study sets the consistency threshold to 0.8 and the frequency threshold to 1, combined with a PRI consistency greater than 0.7, for the calculation of combinatorial paths. Based on fsQCA, three types of solutions with different levels of complexity are obtained: complex solution, parsimonious solution and intermediate solution, where the complex solution is the actual observed case without logical residuals; the parsimonious solution incorporates all possible logical residuals; and the intermediate solution is based on the two, which is the logical residuals combining the theoretical and practical ones.

In this paper, with reference to the intermediate solution and supplemented by the parsimonious solution, a total of five effective paths that generate high innovation and entrepreneurship activity and three paths that generate non-high innovation and entrepreneurship activity are derived from the group state analysis, as shown in Table 3.

Table 3: Configuration of high and non-high activity of innovation&entrepreneurship

	High IEA(N=178)					Non-high IEA(N=346)		
	H1	H2	H3	H4a	H4b	NH1	NH2	NH3
Theoretical teaching	●	●	▲	▲	▲	△	○	●
Teacher allocation	▲	▲	○	△	△	○	△	●
Practical activities	▲	○	●	▲	▲	△	●	○
Service platform	○	▲	●	●	○	●	△	▲
Incentive policies	●	▲	▲	▲	▲	○	▲	△
Cultural atmosphere	○	●	○	○	●	▲	○	△
Consistency	0.892	0.885	0.828	0.879	0.864	0.901	0.894	0.882
Original coverage rate	0.568	0.539	0.356	0.634	0.495	0.476	0.549	0.386
Consistency of solution	0.869					0.817		
Coverage rate of solution	0.733					0.784		

▲ indicates that the core condition exists, △ the core condition does not exist, ● indicates that the edge condition exists, and ○ indicates that the edge condition does not exist.

Path H1 can be summarized as faculty-practice-driven, whose core conditions are faculty allocation and practical activities, with theoretical teaching as a marginal condition, even if perfect innovation and entrepreneurship service platforms and active innovation and entrepreneurship cultural atmosphere cannot appear at the same time, it can still enhance innovation and entrepreneurship activity in colleges and universities, and the consistency of this path reaches 0.892, with an original coverage rate of 0.568;

Path H2 is high faculty supplemented by incentive-service-led, this path in the absence of rich practical activities can still be well led to high innovation and entrepreneurship activity, the consistency of the path reaches 0.885, the original coverage rate is 0.539;

Path H3 is the teaching-incentive integration type, with theoretical teaching and incentive policies as the core, and practice and platform as the auxiliary support, which can still achieve high innovation and entrepreneurship activity level when there is a lack of faculty allocation and cultural atmosphere. The consistency under this path reaches 0.828 and the raw coverage is 0.356;

Paths H4a and H4b can be attributed to the teaching-incentive-practice triple parallel type, which can still enhance the innovation and entrepreneurship activity level of college students under the condition of lack of high faculty configuration, or even when there is insufficient service platform or cultural atmosphere, as long as the theoretical teaching, activity practice, and incentive policy and are the core conditions;

Aggregate to non-high innovation and entrepreneurship activity group state analysis, the results of fuzzy set qualitative comparative analysis is not completely follow the law of causal symmetry. The group states leading to non-high innovation and entrepreneurship activity are categorized as double-deficient type of teaching and practice, double-weak type of faculty and service, and double-deficient type of incentives and culture.NH1 indicates that when the theoretical teaching in school is detached from practice and at the same time practical activities are very scarce, even if the school has a good cultural atmosphere and service platform, it is still difficult to really stimulate students' innovation and entrepreneurship actions; NH2 oriented to the lack of high faculty allocation and service platform, under the Even if there are incentive policies to encourage innovation, it still can't be oriented to high innovation and entrepreneurship activity; NH3 reveals a state of indifference in the absence of incentive policies and cultural atmosphere, even if the school establishes a complete service platform, it can't achieve the purpose of improving the quality of innovation and entrepreneurship education in colleges and universities.

3 Learner Course Profiling and Resource Recommendation Based on Online Learning Space Modeling

From the results of the above group analysis, the model of online learning space supporting innovation and entrepreneurship practice is constructed, and through data collection, learner profile construction and course recommendation technology, accurate matching and personalized support regarding innovation and entrepreneurship education resources are realized.

3.1 Model construction of online learning space based on innovation and entrepreneurship education

The purpose of the creation education in colleges and universities is to promote the improvement of students' practical ability and innovation ability. Students have to go through the spiral growth process of knowledge acquisition, knowledge internalization and knowledge regeneration in the process of receiving education. Network learning space can provide the environment and resource support for the development of innovation and entrepreneurship education in colleges and universities, and the specific functional model is shown in Figure 1, which is the technical support layer, the functional module layer, the practical activity layer and the result generation layer from the bottom up respectively. This paper focuses on the first two modules.

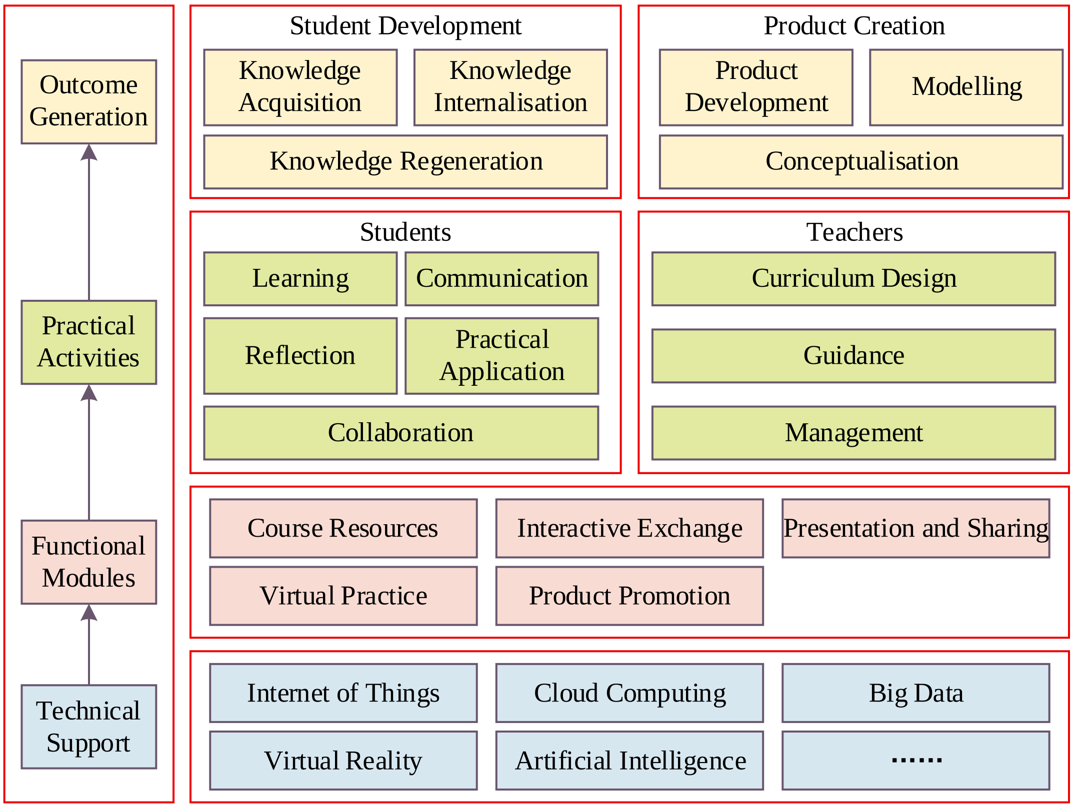


Figure 1: Space model of online learning on innovation&entrepreneurship education

3.1.1 Technical support layer

Network learning space can make comprehensive use of Internet of Things (IoT), cloud computing, big data analysis and other integrated technologies to realize high-efficiency information storage, management and exchange mechanisms, and provide intelligent and personalized services for users. The overall architecture of the current e-learning space basically consists of an infrastructure platform layer (IAAS), a platform service layer (PAAS), a software service layer (SAAS) and a resource service layer (RAAS), and it can support the use of multiple terminals such as PCs and smartphones. In addition, the development of various information technologies such as virtual reality, artificial intelligence, learning analytics, data mining, etc. all provide richer opportunities and more diversified tools for the development and practice of creativity education. A variety of technologies are jointly encapsulated into a unified service platform to provide users with teaching resources and services.

3.1.2 Functional module layer

The essence of creativity education is an educational activity, which requires the integration of online and offline teaching resources, and the development of multiple teaching links such as course lectures, course guidance and Q&A, course activities and practices, interactive exchanges, and comprehensive evaluation. On this basis, it also focuses on the comprehensive cultivation and enhancement of students' scientific literacy, innovative spirit and creative ability. In view of this, the functional modules of the network learning space need to include multiple modules such as curriculum resources, interactive communication, virtual practice, display and sharing, and product promotion, reflecting the concept of creativity education which is fundamental to ability enhancement and oriented to product innovation. Among them, the curriculum resource module is to provide students with all kinds of courses that can enhance innovation and creativity. Compared with traditional curriculum resources, these courses have the characteristics of interdisciplinary, operable, intelligent and contextualized, etc. Teachers can upload microcourses, SPOC, etc. through the online learning space, and students can customize personalized courses according to the needs and regulate the learning progress by themselves. Innovation is a social activity that requires social learning and teamwork, and the interactive communication module can play the role of creative dispersion and effective reorganization and clustering of resources. The virtual practice module integrates artificial intelligence, augmented reality, computer simulation, 3D printing and other Internet and media technologies to provide users with personalized learning environments that are similar to real workshops but break the time and space constraints, with highly contextualized and low-cost features. The display and sharing module is to provide a platform for students participating in creativity education to display their creativity and achievements, and to realize the exchange and collision of ideas, knowledge and creativity in the process of displaying in the virtual space, which is conducive to the correction and perfection of the products and the revision of the learners' thoughts. The product promotion module is a necessary part of the development of creativity education, which creates an atmosphere of innovation and entrepreneurship in a comprehensive online environment of schools, society and enterprises.

3.2 Data Collection on Innovation and Entrepreneurship Education

The data about innovation and entrepreneurship education collected in this paper are obtained through sensors and dynamic scripts, including classroom recording data, learning behavior data, team seminar exchange data, etc., with real-time and unstructured characteristics. On-campus business system data are obtained through student management system, teaching management system, research management system, experiment management system and other business systems, with structured and semi-structured characteristics. Third-party data are obtained through off-campus Internet, academic websites, social media, and research by third-party data organizations, which are characterized by heterogeneity and uncertainty. Through the collection and organization of these big data, the whole picture of individual students in innovation and entrepreneurship education can be reflected in an all-round way, and it is the basic work for the portrait of students.

The following is a description of the composition and sources of student portrait data in the field of innovation and entrepreneurship education

(1) Natural attributes: the description of basic information of students. It mainly comes from the student management system, including name, gender, faculty, grade, specialty and so on;

(2) Offline learning behavior: description of classroom learning of innovation and entrepreneurship related courses and professional courses. Mainly from from the faculty management system, sensors, classroom recordings, etc.. Including learning attitude (SA), classroom performance (CP) and final study results (FS);

(3) Online Learning Behavior, a description of online learning behavior on the Internet, including web browsing (WB), web bookmarking (WBM), database access record (DAR), document downloading (DD), online reading (OR), and distance learning training (DLT). Sourced from historical search records, user logs, library systems, etc.

(4) Innovation and Entrepreneurship Behavior: description of participation in innovation and entrepreneurship activities and competitions, including Innovation and Entrepreneurship Project Undertaking (IEPU), Extracurricular Practical Activity (ACPA), Entrepreneurship Practice (EP), Attitude of Participation (APA), Performance of Participation (PPA), and so on. The data come from teaching management system, research management system, team members, instructors, colleges or departments, innovation and entrepreneurship bases, etc.

(5) Innovation and Entrepreneurship Achievements, a description of innovation and entrepreneurship performance. It includes patent applications (PA), competition awards (CW), transformation of results (TS), etc. It mainly comes from the special website of innovation and entrepreneurship education.

3.3 Online Course Resource Recommendation Method Based on Learner Profiling and Deep Confidence Networks

Based on the collected multi-source data of students' innovation and entrepreneurship, the study further proposes a recommendation method that integrates course portrait and deep confidence network, and realizes personalized education resources recommendation using the above data.

3.3.1 Representation of Model Inputs Incorporating Course Portraits and Learner Portraits

The input of the deep confidence network recommendation model uses the combination of learner and course features to form a “learner-course” feature matrix, which requires the combination of features related to the learner's profile such as the learner's basic information, learning interest, learning ability, and learning intention, and features related to the course's profile such as the course's basic information, difficulty of the course, quality of the course, and characteristics of the course. The following is a general description.

Remembering the set of learners L, the set of course resources C, the set of learning interests I, the set of learning abilities A, the set of learning intentions P, the set of course difficulties D, the set of course qualities, the set of Q course characteristics F, and the extensible information $Info$, the representation of the model's input features is as shown in Equation (5):

$$Input = L \cup C \cup I \cup A \cup P \cup D \cup Q \cup F \cup Info \quad (5)$$

The *Info* denotes the course introduction text and course review text. The recommendation algorithm model inputs the word vectors of the course introduction text and course review text at the same time as the features related to the course portrait, which can reduce the error caused by feature extraction.

The “learner-course” feature matrix is input into the course recommendation algorithm model, in which there is a large correlation between the learner's learning interest and the course category, between the learner's learning ability and the difficulty of the course, and between the learner's learning intention and the course features, and it is expected that using the combination of the learner and course features as inputs to the course recommendation algorithm model can improve the recommendation results. It is expected that using the combination of learner and course features as inputs to the model can improve the quality of the recommendation results.

3.3.2 Implementation of Online Course Resource Recommendation Method Based on Learner Profiling and Deep Confidence Networks

Since the “learner-course” feature matrix is a sparse matrix with huge dimensions, traditional recommendation algorithms cannot solve the problem of data sparsity, and the multilayer network structure of deep neural network has strong feature learning ability and feature extraction ability, taking into account the characteristics of the model and the applicability of the current scenario and other factors, this study uses the method based on Deep Belief Network (DBN), whose network structure is shown in Figure 2.

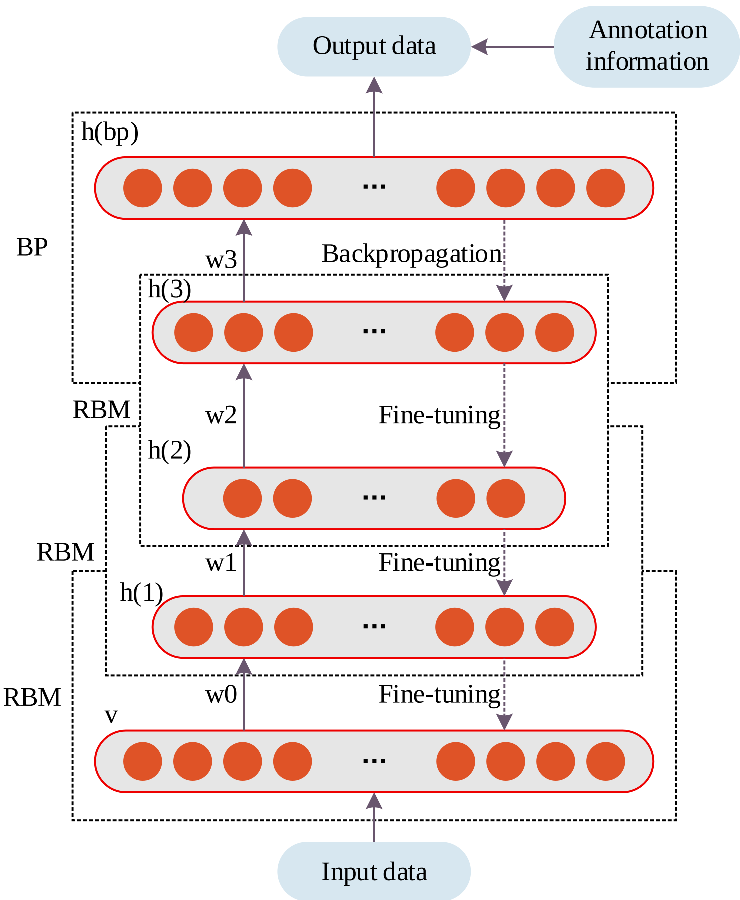


Figure 2: DBN network structure

DBN is a probabilistic generative model, which is essentially a neural network containing multiple hidden layers, each of which consists of a Restricted Boltzmann Machine (RBM), to mine and discover the deeper expression of the features by extracting the features layer by layer from the original data.The training process of the DBN consists of two parts, namely, unsupervised pre-training and supervised parameter fine-tuning, and the corresponding flowchart is shown in Fig. 3.

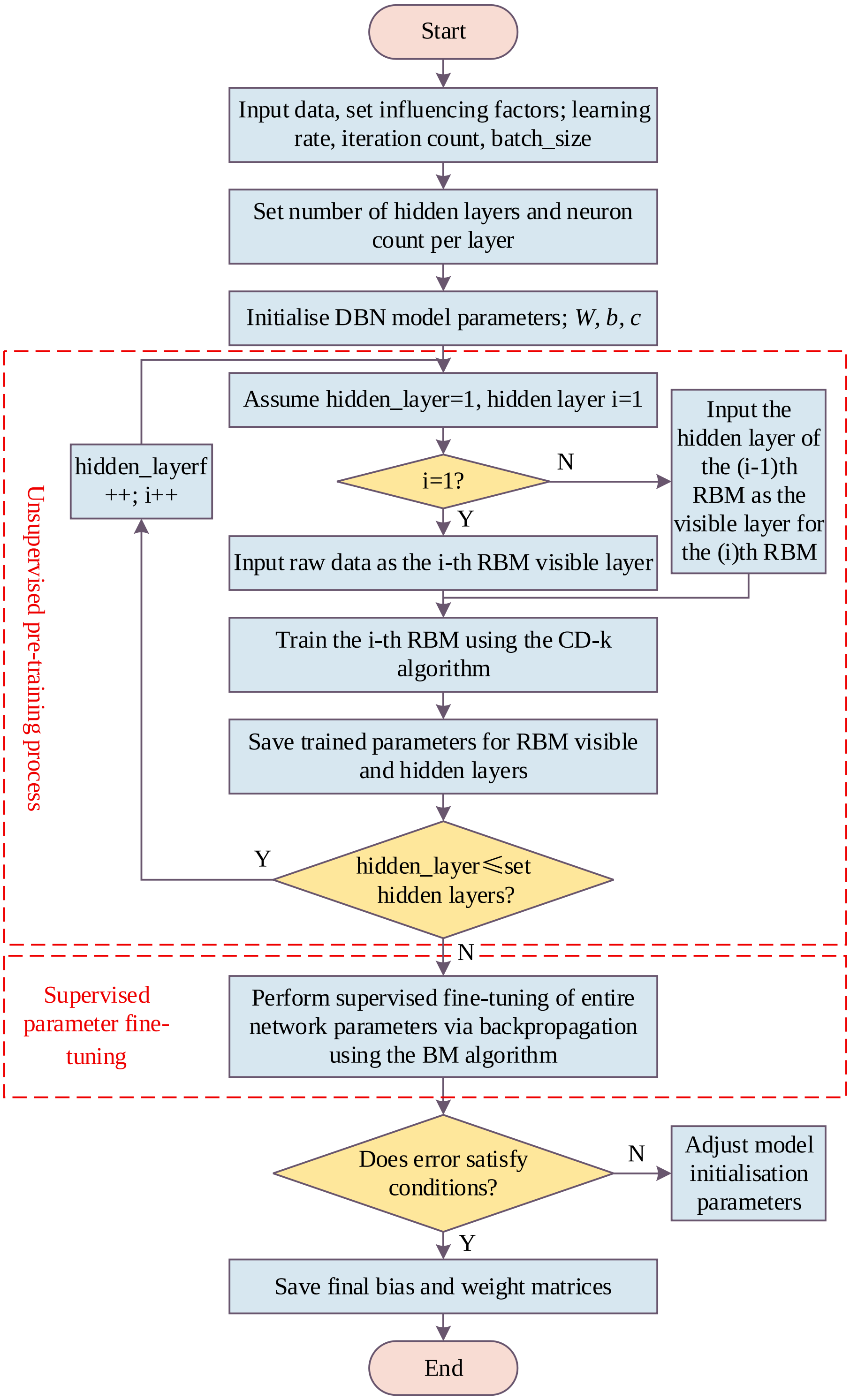


Figure 3: The process of DBN pre-training

Each "learner-course" feature vector constitutes an independent RBM submodel, and the number of neurons in its visible layer is the number of attributes of the "learner-course" feature vector. In the unsupervised pre-training process, the first input is unlabeled training data, and for each layer of the RBM network, the unsupervised method is used to train the RBM network from the bottom upwards, and the output of the previous hidden layer of the RBM is used as the input of the next layer of the RBM, and the CD-k algorithm is used to ensure that each layer of the RBM ensures the optimization of its own parameters, and then the parameter matrices of each layer of the RBM are saved. Then supervised parameter fine-tuning is performed, the back propagation network is located in the last layer of the DBN network, the input vector of its visible layer is the output feature vector of the last hidden layer of the RBM, and combined with the course preference scoring labels, so that each layer of the RBM accepts the error information from the back propagation network, which in turn fine-tunes the parameters of the entire RBM network, and when the training error meets the set threshold, the logistic regression classifier is used to The output layer of the DBN network is classified to obtain the learner's preference prediction score for the course.

At the end of model training, an expression model for learning learners' preference scores for course resources is constructed from the set of parameters Θ of each layer saved during the training process, and the model outputs a list of recommended courses, which are ranked from high to low according to the predicted scores of course preferences, and recommended to the target learners.

4 Recommendation of Innovation and Entrepreneurship Education Resources Based on Clustering and Learner Portrait

Based on the above 524 students, combined with the innovation and entrepreneurship education data in section 3.2, the behavioral data of students in four aspects: offline learning behavior, online learning behavior, innovation and entrepreneurship behavior and innovation and entrepreneurship achievements are deeply mined. Cluster analysis is used to identify different types of student groups from the two core dimensions of academics and practice. Then, based on more multi-dimensional innovation and entrepreneurship behavior data, a refined learner portrait is constructed. Finally, the portrait is integrated into the DBN recommendation model, and its effectiveness in accurately matching course resources is verified through comparative experiments.

4.1 Cluster analysis based on students' innovation and entrepreneurship education data

4.1.1 Cluster analysis based on academic performance and extracurricular practical activities

First, 524 students were clustered and analyzed based on their final academic performance in offline behavior and extracurricular practical activities in innovative and entrepreneurial behavior (both in percentage). A total of five clusters were divided into five clusters, and the distribution of students' performance in both areas is shown in Figure 4. Where the Z-axis is the students' extracurricular practical activities achievement, while the point size is also indexed to the practical activities achievement, and the Y-axis is the students' final examination achievement.

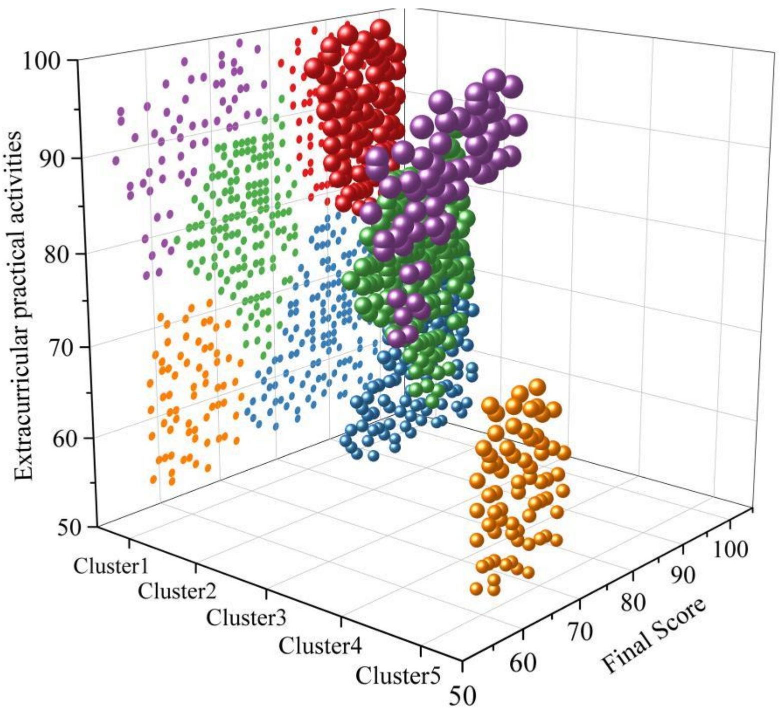


Figure 4: The distribution of final scores and performance in practical activities

Based on Figure 4 it is clear to see the difference performance of five clusters in innovation and entrepreneurship education.

Cluster 1 leads in both academic achievement and practical activities and is located in the upper left corner of the graph, with its average scores for both being 90.92 and 88.65. Naming this cluster of students as the Overall Leader type.

Cluster 2, with 146 students, can be seen in the Y-Z projection in the lower right corner of the graph, and is of the type with outstanding academic achievement (mean score of 88.93) but significantly low participation in practical activities (mean score of only 64.70), which is named as the academically focused type.

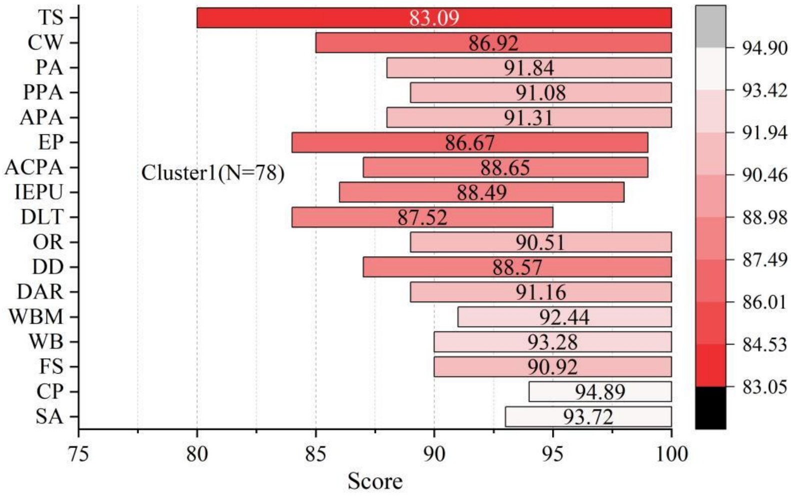
In contrast, cluster 4 located in the upper left corner, N=63, which has a larger bubble point, that is, this type of students in the practical activities situation performance is better, an average of 90.03, but its academic relative shortcomings, the final grade average is only 66.64, called this type of students as practice-oriented type.

Focusing on cluster 3 with the largest number of points (N=169), which represents an intermediate state, students in this category have almost all academic and practical scores in the 70-80 range, calling this category developmentally balanced.

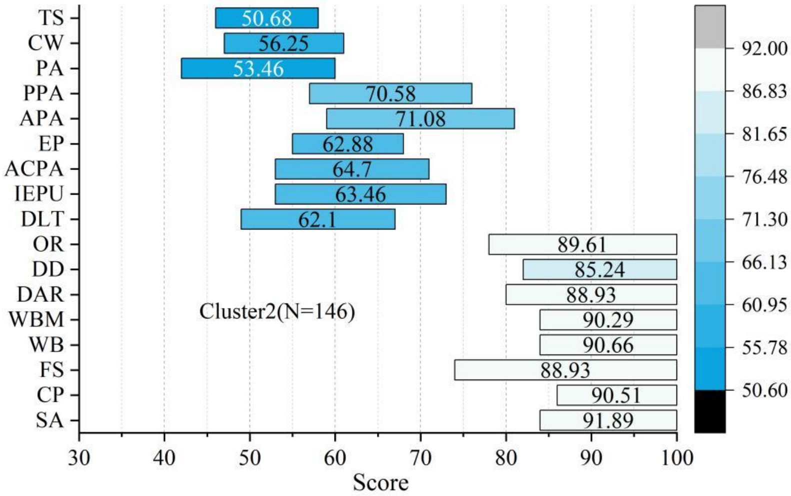
Cluster 5, which is located in the lower left corner, is in the low position in both dimensions, with an average academic and practical score of and 61.09, which is a group that needs to be focused on and assisted, and is a developmental lag type.

4.1.2 Different clusters of students in innovative and entrepreneurial education data

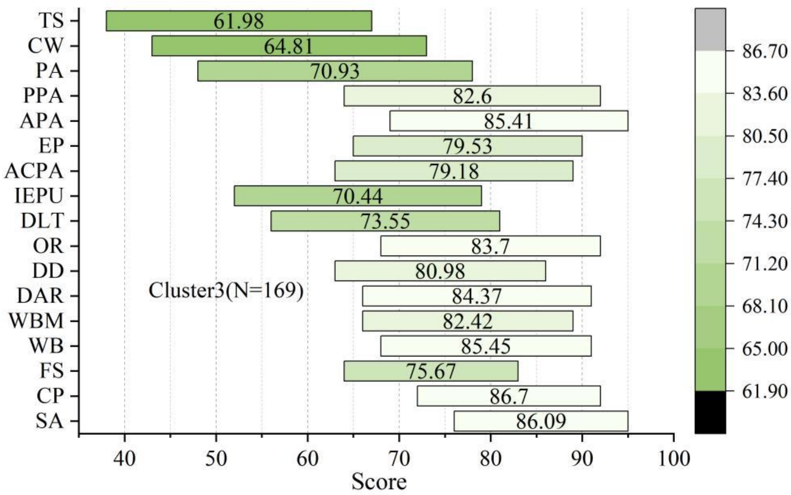
Based on the above clustering division, other data in the collected data on innovation and entrepreneurship education are now analyzed.The data distribution of the five clusters of students in terms of learning attitude, web browsing, and innovation and entrepreneurship project undertaking is shown in Figure 5. All data are processed by percentage system, and the labeled data show the average value of each cluster score.



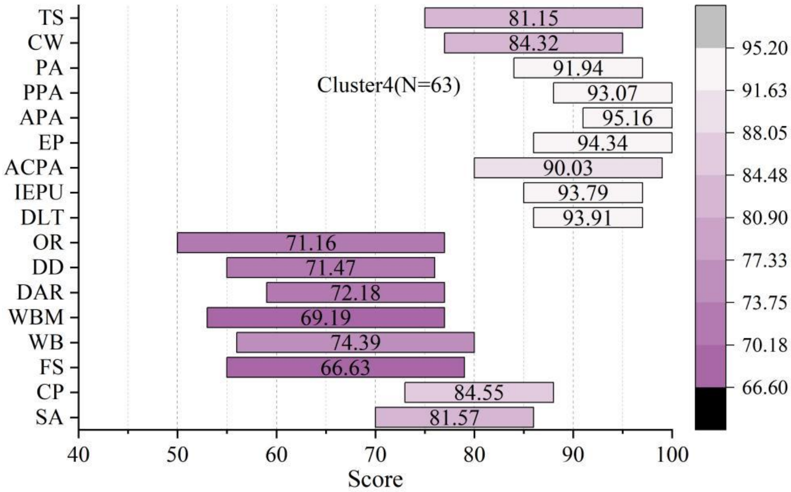
(a)Cluster 1(N=78):Comprehensive Leading Type



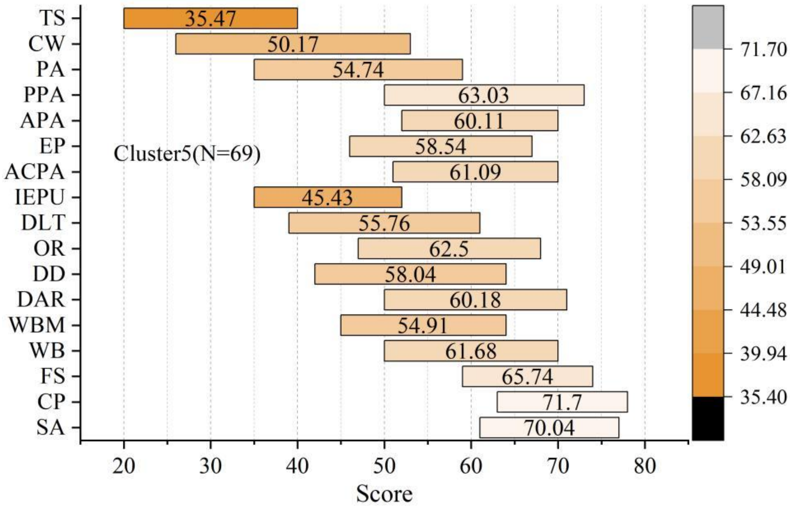
(b)Cluster 2(N=146):Academic-focused Type



(c)Cluster 3(N=169):Balanced Development Type



(d)Cluster 4(N=63):Practical-oriented Type



(e)Cluster 5(N=69):Lagging Development Type

Figure 5: Distribution of 5 clusters students of IEE datas

Distribution of students in other educational data, further arguing for the correctness of the study's clustering classification.

As shown in Figure 5(a), Cluster 1 continues its comprehensive leading qualities, maintaining a high level of balance on all indicators of the first eight online and offline learning behaviors, with scores generally in the [90,100] range. At the same time, it also has a bright performance in innovation and entrepreneurship behavior and results output indicators, IEPU innovation and entrepreneurship project undertakings average score of 88.49, the average patent application is also 91.84, this type of students can be transformed into the practical results of what they have learned to achieve the integration of learning and practice.

Figure 5(b) Cluster 2 Academically Focused Students once again confirms the differentiation pattern of strong academics and weak practice. Their first eight indicators are all concentrated to the right, the score range is almost all between [85,100], and the average score of each indicator of learning behavior is almost all around 90. But aggregated to the practice area, the data is significantly lower, online learning behavior DLT distance learning training participation average score is only 62.10, IEPU innovation and entrepreneurship program scores an average of 63.46, EP entrepreneurial practice 62.88, results of the transformation is as low as 50.68. this type of students are more accustomed to the traditional path of learning, the expansion of the form of practical learning participation is limited.

Cluster 3 balanced type scores mostly fall in the middle range of 60-90 points (innovation and entrepreneurship achievement scores are lower and more widely distributed, [40,80]). Students in this category have a certain amount of learning input and practical activity participation, but the output of innovative outcomes is relatively limited, such as CW competition awards and TS outcome transformations are only 64.81 and 61.98.

The practice-oriented mapping of cluster 4 shown in Fig. 5(d) contrasts with cluster 2, where the distribution of the first eight learning behavior indicators is to the left (with an interval between [55,80]) while the scores of the innovation and entrepreneurship indicators are to the right. Their DLT distance learning training), IEPU innovation and entrepreneurship program undertaking, EP entrepreneurship practice and APA participation attitude mean scores are 93.91, 93.79, 94.34 and 95.16, respectively, which are more than 90, and they have achieved considerable results through high-intensity practical inputs, and 91.94 for PA patent application.This group of students, although they are relatively neglectful of academics, have achieved very good results in their innovation and entrepreneurship education, they have achieved very good results.

Cluster 5 Lagging development type is in the low position in almost all dimensions, especially in innovation and entrepreneurship results are obviously weak, 69 students in the results of the transformation of the average score of only 35.47, and even some learners only achieved 20 points. This group has deficiencies in motivation and ability to participate in learning and innovation and entrepreneurship as a whole, and is negatively burned out.

4.2 Learner profile output based on innovation and entrepreneurship data

Based on the above mentioned 4 categories and 17 items of innovative and creative data, the study constructs a learner portrait for this, which is presented in a visualized form. Figure 6 shows the output of a learner portrait based on innovative and creative data.

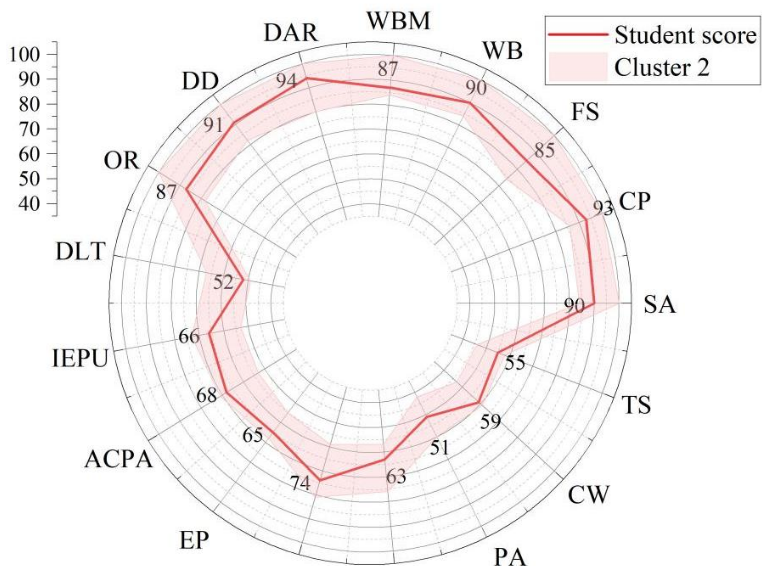


Figure 6: Output of a learner profile based on innovative and creative data

Each of the scores of this learner belongs to the score range of Cluster 2 students, and the learner portrait in Figure 6 outlines a typical academically focused student. The student's online and offline learning behaviors are relatively solid, with CP classroom performance, DAR database access records, and literature downloads at 93, 94, and 91, respectively, which are perfectly in the high scoring intervals of [86,100], [90,100], and [82,100] in Cluster 2. At the same time, the portrait also reveals the obvious shortcomings in the practical aspects of the student. All the indicators directly related to innovation and entrepreneurship, from the 52-point DLT distance learning training, to the 66-point IEPU innovation and entrepreneurship program undertaking, to the final 55-point TS results transformation, scored significantly lower than their academic performance. Once again, it confirms that this academic focused characteristic: although it performs well in learning behaviors, it is far from actively participating in innovation and entrepreneurship practice, and is in a low-frequency wait-and-see state, failing to effectively transform its academic strengths into innovative outputs.

4.3 Course Recommendation Performance Comparison Experiment

In order to further validate the practical utility of this paper based on learner portraits and deep confidence network (DBN) in recommending innovative entrepreneurship education course resources, 524 learner portraits derived from the above are input into the model, and comparative experiments are carried out based on both portrait similarity matching and DBN model prediction.

User Collaborative Filtering (User-CF) and Matrix Decomposition-based Hidden Semantic Model (SVD) were selected as the comparison models. Ten experiments were conducted using each model separately.

4.3.1 Portrait Similarity Matching Analysis

The similarity matching results of student portraits under three different recommendation algorithms are shown in Fig. 7.

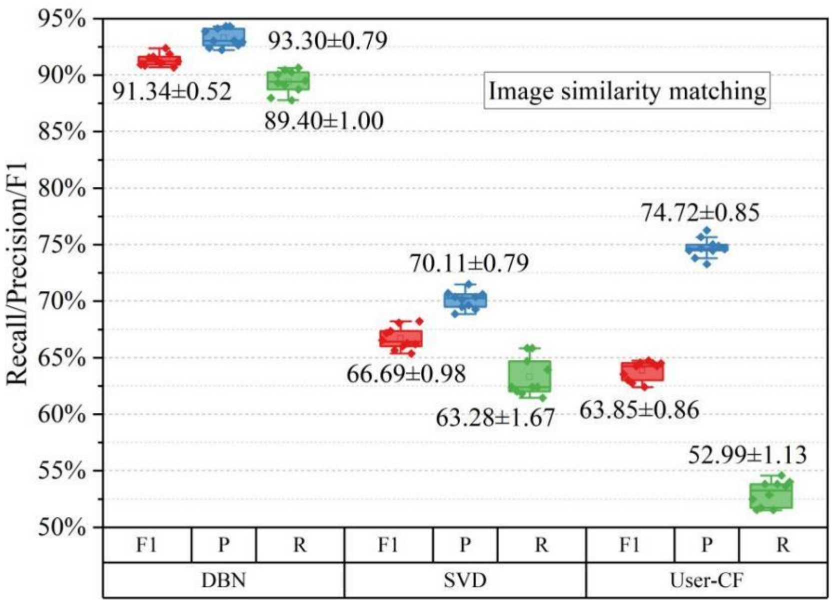


Figure 7: The matching results of student profiles based on 3 algorithms

Ten experiments under the user-based collaborative filtering algorithm matched 270 to 283 portraits, respectively, with recall rates between 51.52% and 54%, precision rates between 73.28% and 76.27%, and F1 averaging 63.86%, whereas the matrix decomposition-based steganographic semantic model (SVD) had an average recall rate, precision rate, and F1 of

63.28%, 70.10%, and 66.69%, this paper recognizes 461-474 learner portraits with an average accuracy of 93.29 and F1=91.34% in ten experiments based on learner portraits and under the Deep Belief Network (DBN) recommendation method.

Methods such as User-CF and SVD rely on the explicit user-course interaction matrix, which has limited ability to capture complex nonlinear relationships when facing the high-dimensional sparse data covering multi-dimensional portrait features such as learning attitude and practice behavior constructed in this paper, resulting in insufficient matching accuracy. In contrast, the DBN model performs deep unsupervised feature learning and extraction of heterogeneous learner portrait features through its multi-layer Restricted Boltzmann Machine (RBM) stacking structure. It mines out students' deep knowledge structure preferences, thus realizing more accurate portrait similarity measurement and matching.

4.3.2 Analysis of model prediction results

The prediction results under different recommendation algorithms in 3 are shown in Fig. 8.

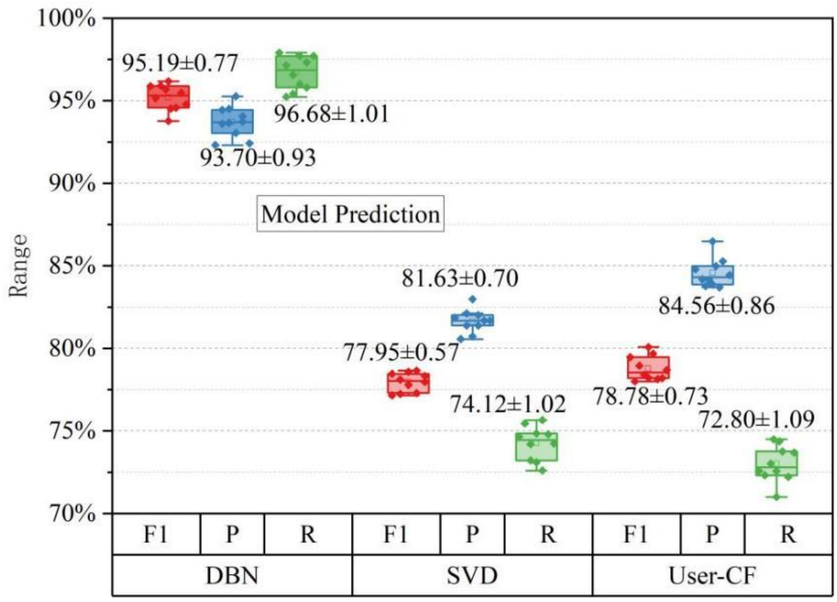


Figure 8: Analysis of model prediction results based on 3 recommendation algorithms

For the final innovation and entrepreneurship education course recommendation prediction, the superiority of the DBN model in this paper is further demonstrated. Its recall ranges from 95.23% to 97.90%, which means that ten experiments successfully obtain course predictions from 499-513 learners respectively, with an accuracy between 93.21% and 95.26%, and an average F1 value of 95.19±0.77, which is 20.83% higher than the 78.78% and 77.95% of User-CF and SVD, respectively, and 22.12%. The extremely high prediction performance of the model in this paper is attributed to the two-stage training mechanism of DBN prediction practice + fine-tuning. In the first stage of unsupervised prediction practice, the model has learned the generalized distribution pattern in the “learner-course” feature space from a large amount of unlabeled data. In the second stage of supervised fine-tuning, the model utilizes back-propagation algorithm to fine-tune the network parameters with specific course preference scoring labels. This process enables DBN to not only deeply understand the complex association between learner profiles and course profiles, but also accurately predict the preference ratings of specific learners for unseen courses.

5 Conclusion

The study depicts the realistic path of improving quality and efficiency of innovation and entrepreneurship education in the digital era through the progressive exploration of histogram analysis-group clustering-portrait construction-intelligent matching.

The fsQCA group analysis reveals five highly active paths, and the high faculty-motivation-service dominant type covers 53.9% of highly active students.

Cluster analysis classified the 524 students into five distinct profiles. 146 academically focused students excelled academically with an average final grade of 88.93, but their average extracurricular practice score was only 64.70. In contrast, 63 practice-oriented students, with their extremely high enthusiasm for practice (average score of 90.03) and output of results (average score of 91.94 for patent applications), were able to partially compensated for the relative shortcomings in academic performance (average 66.63).

The DBN recommendation model based on deep learner profiling shows a significant advantage of F1=95.19% in the course matching experiment, which is able to understand the differences between different categories of students and give students accurate and practical recommendations of innovation and entrepreneurship course resources based on the combination path.

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