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Construction of Students' Innovation Ability Portrait for Cultural Intelligence Computing

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ABSTRACT

At the age of artificial intelligence, the inheritance and development of innovation culture are crucial for constructing an innovative country, and they are major components of cultural intelligence computing. The portrait of innovation ability is a digital representation of innovative culture, and its accurate description is the basis for the personalized cultivation of innovation ability. Therefore, how to objectively and accurately design a labeling system for an innovation ability portrait and depict a high-pixel portrait is an urgent problem to be solved for the digital representation of innovation culture. To address this problem, based on innovation theory, our study (1) uses a combination of subjective and objective methods to design an innovation ability evaluation system, (2) constructs a scientific and reasonable portrait label system, (3) represents the system's results as individual students' innovation ability portraits and student groups' innovation ability portraits, and (4) visualizes the portraits' results. Finally, considering resource recommendation as an example, this study (1) adopts a computational model of crowd intelligence computing, (2) designs and implements a personalized recommendation system for educational resources based on the resulting innovation ability portraits, (3) improves the computing efficiency, and (4) expounds the applications of portraits in personalized learning, precise teaching, and smart educational decision-making to promote personalized innovative talent training and realize the core value of innovative culture.

KEYWORDS

cultural intelligence computing; innovation ability portrait; evaluation index; portrait label system

Cultural intelligence computing[1] employs big data and artificial intelligence technologies to promote the construction of cultural wisdom data and the digital and formal transformation of cultural expressions and related knowledge. It is a key path for cultural protection and inheritance and a realistic demand for digital continuation. With respect to the intelligence age, the use of intelligent technology to cultivate innovative talents is the primary function of innovation culture, which is an important factor that affects our country's overall innovation level. Innovation ability is a recognized indicator for evaluating innovative talent. Therefore, creating digital representation and intelligent application of innovation ability to promote the cultivation of innovative talent has currently become a core issue.

User portrait technology is a form of implementing cultural intelligence computing. It involves a process for evolving cultural resources into digital representation and analytical applications of intelligent cultural services through four stages, namely, cultural digitization, cultural dataization, cultural visualization, and cultural intelligence. User portrait technology uses modern information technologies, such as intelligent terminals, 5G networks, big data, and artificial intelligence, to conduct data collection and knowledge mining for users' attribute information and behavior traces[2]. Its implementation must proceed via four stages: information quantification, label construction, label visualization, and intelligent portrait application. The technical architecture of user portrait technology is shown in Fig. 1.

The students' innovation ability portrait is aimed at presenting their innovation ability information in the form of labeling, and it realizes the digital representation of innovation ability. Its precise portrayal is the basis for achieving personalized training of innovative talents and the key to realizing the core values of the university innovation culture. Undeniably, our society is fully affected, transformed, and shaped by ubiquitous, interconnected, and personalized services[3]. Taking the students' innovation ability portrait construction as an example, our research explores the digital representation method of students' innovation ability and its application in intelligence computing of university innovation culture. The label design of students' innovation ability portrait and the division of the granularity of innovation ability directly affect the quality of students' innovation ability evaluation and portrait construction. Using a high-level innovation ability evaluation system, we can design a high-quality innovation ability label system and high-pixel innovation ability portraits. Therefore, constructing a scientific and reasonable evaluation system of innovation ability and designing an accurate image label system of innovation ability are the key issues studied in this research.

In view of this, we took postgraduate students majoring in computer science as the research subjects and combined the characteristics of computer science through subjective experiences, such as expert and student experiences, with objective analysis

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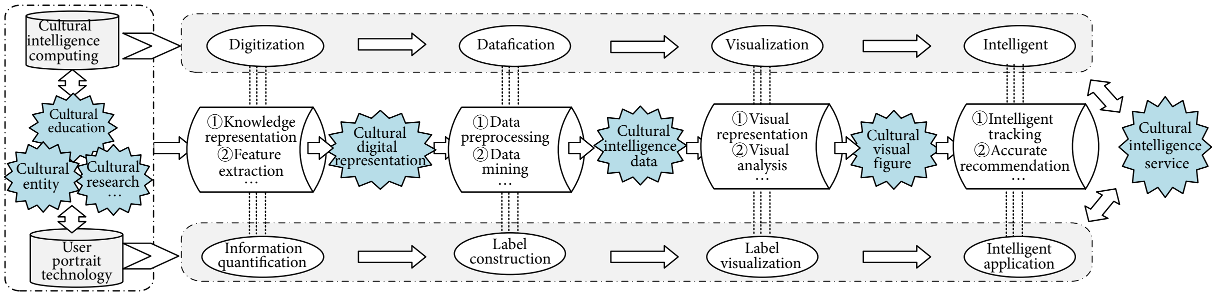

Fig. 1 Technical architecture of cultural intelligence computing and user portrait.

methods, such as exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), to construct an evaluation index system of the postgraduate students' innovation ability. Then, based on the constructed evaluation index system, we adopted cluster analysis and factor analysis methods to design the innovation capability portrait label system. Afterward, this paper presents individual students' innovation ability portraits and student groups' innovation ability portraits through visualization technology to provide an intuitive reference for the personalized cultivation of innovation ability. Finally, this article elaborates on the application of innovation ability portraits in personalized learning, teaching students according to their aptitudes, and intelligent educational decision-making. In addition, taking the recommendation of educational resources as an example, this article designs and implements a personalized recommendation system for educational resources based on the innovation ability portrait. Then, it verifies the application of the recommendation system and shows that the system can provide precise services for students and intelligent services for teachers.

1 Related Overview

1.1 Cultural intelligence computing

Cultural intelligence computing is the application of cutting-edge intelligent information technologies, such as machine learning, data mining, artificial intelligence, virtual reality, statistical learning, and visual analytics, in the field of culture. It is used as a method to explore cultural development rules, prompt internal connections, and display quantitative analysis and presentation of relevant data. Cultural intelligence computing's purpose is to realize a cultural digital transformation, promote culture's migration from the real world to the digital space, and promote excellent culture's continuation in the digital space[1]. Most research works on cultural computing at home and abroad are performed from the following perspectives:

Perspective 1 is cultural computing's research content. At present, it is focused on cultural gene extraction, gene bank construction, cultural quantification, and visual analysis of culture. For example, Te[4] proposed S-MusicXML, a scoring model that can directly and clearly describe music genes and can facilitate the application of data mining technology. Tao et al.[5] quantified the intensity of Chao cultural characteristics through word frequency statistics. Zhu[6] digitally realized birch-bark-making skills through bit-based representation and designed and implemented a digital birch-bark-drawing system with gesture interaction.

Perspective 2 is the cultural computing research field. At present, most studies are performed in the disciplines of art, archaeology, and history on different topics, such as music[7], paper cutting[8], painted pottery[9], birch-bark-making[6], and dress pattern creation[10]. However, there is little research on intelligence computing in the cultures of education, such as the culture of innovation.

1.2 Portrait of students' innovation ability

Student portraits are the application of user portraits in education[11]. A student portrait is a label set generated after cleaning, statistics, conversion, analysis, and processing of student data. The student portrait label is a visual representation of the division result of the students' attribute characteristics[12] and can produce clear visualization effects[13]. Therefore, label design has become a key to portrait construction, and its formulation must rely on the characteristics of students' different dimensional data and classification results. Related research at home and abroad is performed from the following perspectives:

Perspective 1 is portrait label design content. At present, most studies regard students' basic information, such as their names and identification numbers, as static attribute features[14]. Mining and extracting dynamic attribute characteristics are usually based on students' behavioral information, such as action trajectory[15], network behavior[16], and consumer behavior[17]. A student's ability information is constantly updated and changed during the learning process, and it can be regarded as the source of dynamic attribute feature mining. However, because of the difficulty in feature mining and capability data collection, few scholars have studied capability portraits, such as innovation capability portraits.

Perspective 2 is the portrait label design method. Currently, most studies use statistical analysis and data mining algorithms to design labels for students' attributes. Statistical analysis is mainly used for students' structured data. It processes and transforms students' raw data using statistics, such as means, standard deviations, and peak values. A part of the generated statistical data is used as student labels that reflect the overall situation and distribution, and the other part is used as a dimensionality reduction data source for deeper mining and analysis to examine more abstract potential labels. Data mining algorithm analysis includes classification, clustering, association, and natural language processing algorithms, among other analyses[13]. However, these label design methods operate only on collected data in extracting labels. Few scholars first combine the theoretical basis and evaluation index design principles to design label systems while constructing evaluation index systems and then constructing a theoretical and scientific student portrait.

2 Design Framework of Students' Innovation Ability Portrait for Cultural Intelligence Computing

The Internet has ignited humankind's demands and unleashed their potential needs, thus forming the motive power for the Internet and changing the industry and social operation modes[18]. Innovation ability is an important part of the innovation culture system, and portrait technology is one way to realize cultural intelligence computing. This study constructed a design framework for students’ innovation ability portraits for cultural intelligence computing and was designed with postgraduates majoring in computer sciences as the subjects under the guidance of the digital humanistic paradigm and innovation ability theory. It is based on the construction of an evaluation index system, construction of a portrait label system, visualization of the portrait label, and intelligent application of the portrait (as shown in Fig. 2). It is also used to explore and realize the digital presentation and application of intelligence computing in the innovation culture of universities.

The main design steps of students’ innovation ability portraits for cultural intelligence computing are as follows.

(1) **Construction of the evaluation index system.** It has four steps: preliminary construction, correction, verification, and confirmation. Under the guidance of the postgraduate student innovation ability theory, existing evaluation indexes, computer specialty characteristics, and student and expert experience, this study constructed a preliminary draft of an evaluation index system from a subjective perspective. First, based on this perspective, a pretest questionnaire was designed as the data source for the evaluation index system revision process. Second, starting from an objective point of view, through EFA, CFA, structural equation model (SEM) revision, and verification of the evaluation index’s first draft, we determine the standard innovation capability evaluation system.

(2) **Construction of the portrait label system.** According to the label construction priority, portrait labels are divided into the original tag statistical analysis and the statistical tag model analysis. First, this involves designing a formal questionnaire, collecting innovation ability profile data, and preprocessing the data for cleaning and desensitization to obtain the original label. Then, through a basic statistical analysis of the innovation capability information, the fact label can be obtained. Next, using the EFA, CFA, and SEM methods to extract the fact label (or original label) data and using k-means cluster analysis based on the elbow method (EM) to construct the model of the original label, we can discover model labels of innovation ability in different dimensions, comprehensive levels of innovation ability, group type of innovation ability, and average levels of innovation ability in each dimension.

(3) **Visualization of portrait labels.** Through the use of ECharts, a data visualization feature, the label collection is represented as individual students’ innovation ability portraits and student groups’ innovation ability portraits.

(4) **Intelligent application of portraits.** Through the use of recommendations, knowledge graphs, predictions, and other technologies from the perspectives of students, teachers, and schools, the innovation ability portraits are applied to personalized learning, precise teaching, and intelligent educational decision-making to promote the effective improvement of innovation capabilities.

3 Construction of an Evaluation Index System for Innovation Ability

3.1 Preliminary construction of an evaluation index system

3.1.1 Design of the evaluation index system’s first draft

The design of the evaluation index system’s first draft originated

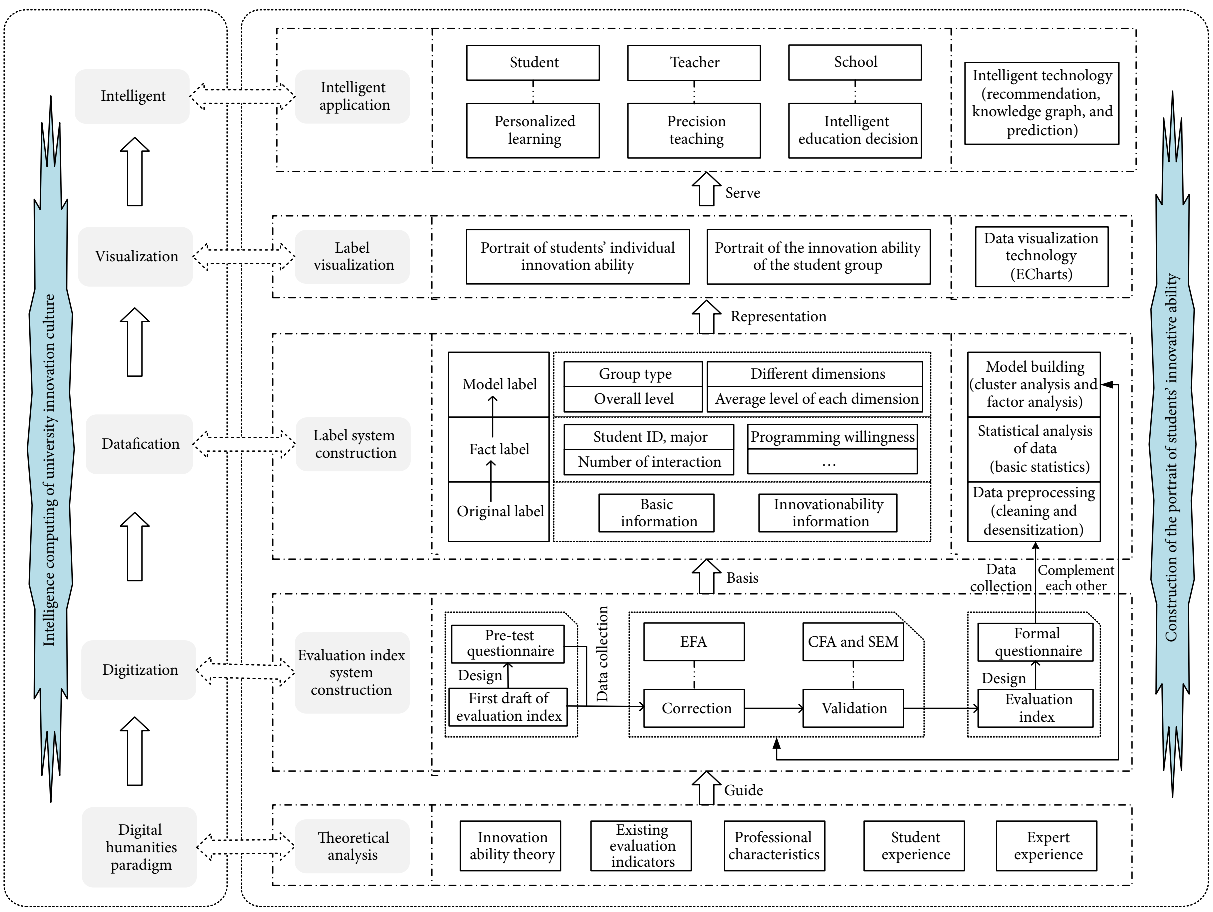

Fig. 2 Design framework of students’ innovation ability portraits for cultural intelligence computing.

from four main aspects: First, it is based on the summary and analysis of existing research. Second, it is based on the professional characteristics of a computer. Third, it is based on the personal experience of postgraduates majoring in computer science, which contributes to supplementing and revising the evaluation index system from the student learning perspective. Fourth, it is based on computer science experts' experience, improving the evaluation index system from the teaching perspective. Therefore, we selected the innovation literacy (Q), knowledge framework (K), team collaboration (C), and innovation practice (A) as the first-level indicators, which were then subdivided to 26 second-level indicators Q_1–Q_9, K_1–K_7, C_1–C_6, and A_1–A_4. The first draft of the evaluation index system that we designed is shown in Table 1.

3.1.2 Design and verification of the pretest questionnaire

Based on the evaluation index system's first draft and referring to a five-point Likert scale, we designed a preliminary survey questionnaire on the creative ability of postgraduate students majoring in computer science. The questionnaire is divided into five parts: basic information, innovative qualities, knowledge learning, teamwork, and innovative practice. To collect sample data, we distributed the questionnaire through the QuestionStar platform to 2019 postgraduate students majoring in computer science at Henan Normal University, Guilin University of Electronic Technology, and Hunan University.

Item analysis involves analyzing the degree of distinction between the questionnaire's questions[19], that is, deleting or modifying inappropriate questions to ensure the questionnaire's scientific nature and guarantee research accuracy. This paper adopted the extreme groups' method to conduct an item analysis on the collected sample data. The results reveal that all questionnaire questions reached the same significance level of 0.000 ($p < 0.01$) and 95% confidence level of the difference between the means excluded 0. Hence, high and low groupings have significant differences in all variables, so all questions have a high degree of discrimination. Therefore, each question can distinguish the response degrees of different respondents, so all items were retained. In addition, we conducted a homogeneity reliability test on the questionnaire, and the results show that the questionnaire's overall Cornbrash's alpha was 0.932 (> 0.7), reaching an acceptable reliability level and indicating the questionnaire's internal consistency.

3.2 Revision and verification of the evaluation index system

3.2.1 EFA of the first-order factors of innovation ability

EFA ensures the original data structure by simplifying variables and levels[20]. For this research, we distributed 218 pretest

Table 1 First draft of the evaluation index for the computer science graduates' innovation ability.

Level 1 indicator	Level 2 indicator	Level 3 indicator
Innovation literacy (Q)	Critical and questioning spirit (Q_1)	Ability to find problems
	Logical thinking (Q_2)	Ability to think and solve problems
	Imaginative thinking (Q_3)	Imagination and activeness of thinking
	Innovation motivation (Q_4)	Innovation psychology and motivation consciousness
	Innovation quality (Q_5)	Curiosity, confidence, adaptability, and responsibility
	Information literacy (Q_6)	Information retrieval capabilities
	Self-study ability (Q_7)	Unique learning method and independent thinking
	Verbal comprehension (Q_8)	Reading comprehension
	Learning comprehension (Q_9)	Innovative inspiration and unique ideas
Knowledge framework (K)	Basic knowledge of mathematics (K_1)	Mathematical basis
	Thesis writing ability (K_2)	Paper-writing ability
	Cutting-edge knowledge (K_3)	Frontier knowledge learning in professional fields
	Professional research methods (K_4)	Professional research methods
	Integrative knowledge (K_5)	Professional cross-fusion knowledge
	Programming knowledge learning (K_6)	Attitude and difficulty of programming learning
	Programming knowledge practice (K_7)	Programming operation ability, programming tool proficiency, and programming language proficiency
Team collaboration (C)	Cooperative consciousness (C_1)	Willingness to unite and cooperate
	Information sharing (C_2)	Willingness to share information
	Self-regulation (C_3)	Attitude toward failure and ability to summarize and absorb experience and lessons
	Communication skills (C_4)	Communication ability and frequency with tutors
	Language expression skills (C_5)	Fluency and organization of language expression
	Listening ability (C_6)	Attitude toward different views
Innovation practice (A)	Research activities (A_1)	"Mathematics Modeling, Challenge Cup, Internet +, etc." professional competition
	Academic conference (A_2)	Experience and frequency of attending academic conferences
	Report lecture (A_3)	Learning experience and frequency of attending academic reports and academic lectures
	Implementation (A_4)	Planning and implementation of solutions

questionnaires and received 211 valid responses. The questionnaire's effective response rate was 96.8%. We used the SPSS software to perform a factor analysis on the questionnaire and discovered the structural characteristics involved in measuring and evaluating innovation ability, thereby simplifying the scale, reducing the number of questions, and ensuring each question's relevance.

(1) We conducted the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity on the questionnaire to determine its suitability for factor analysis. The results are as follows: the KMO value is 0.934, which is greater than 0.9 and close to 1, and the χ^2 value of Bartlett's sphericity test is 3624.214 (210 degrees of freedom; p = 0.000, less than 0.01). These results indicate that there are common factors among variables. Therefore, this set of data is highly correlated and suitable for factor analysis.

(2) We used principal component analysis to extract the common factors, obtained the initial factor-loading matrix, and obtained the rotation factor-loading matrix through the Kaiser standardized optimal skew method. We evaluated the factor analysis results against the following standards: The load value of the test questions is less than 0.50, the commonality is less than 0.30, the common factor is not less than two observation indexes, and each index cannot span two or more common factors. We used these standards to delete inappropriate questions from the questionnaire, leaving 21 usable questions.

(3) Next, we again performed a factor analysis on the remaining items. Based on the criterion that the characteristic value must be greater than 1, combined with the questionnaire's actual meaning, we determined four first-order factors, which explain 73.722% of the total variance. The item load value and common degree are shown in Table 2.

Table 2 Rotated component matrix and common factor variance statistics.

Test question	Factor loading				Common degree
	Common factor 1	Common factor 2	Common factor 3	Common factor 4	
C_2	0.901	–	–	–	0.729
C_6	0.892	–	–	–	0.799
C_1	0.838	–	–	–	0.747
C_3	0.785	–	–	–	0.752
C_4	0.715	–	–	–	0.756
C_5	0.590	–	–	–	0.661
A_2	–	0.962	–	–	0.710
A_4	–	0.822	–	–	0.676
K_2	–	0.820	–	–	0.755
K_3	–	0.764	–	–	0.810
K_4	–	0.674	–	–	0.802
K_1	–	0.615	–	–	0.715
K_5	–	0.556	–	–	0.617
Q_9	–	–	0.850	–	0.804
Q_8	–	–	0.837	–	0.778
Q_4	–	–	0.787	–	0.741
Q_3	–	–	0.766	–	0.697
Q_7	–	–	0.717	–	0.775
K_7	–	–	–	0.842	0.842
A_1	–	–	–	0.765	0.584
K_6	–	–	–	0.685	0.731

Note: The extraction method is the principal component analysis, and the rotation method is the Kaiser standardized optimal skew method. The rotation converged after six iterations.

The first and third factors in Table 2 are from the original factors of the original questionnaire, so their original names are retained. Among them, the first factor, consisting of six test questions, is team collaboration (C), and the third factor, consisting of five test questions, is innovation literacy (Q). However, the original questionnaire's observation test items for the hypothetical factor knowledge framework and innovative practice overlap. Among them, the knowledge framework factor spans the academic meeting and implementation test items, both of which are knowledge-learning methods. Therefore, the second factor, consisting of seven items, is knowledge learning (KA). The innovative practice factor spans the programming knowledge learning and programming knowledge practice items, which form the basis of computer science postgraduate students' scientific research activities. Therefore, the fourth factor, consisting of three items, is programming practice (P). We used EFA to revise the innovation ability evaluation index's first draft and obtained four first-order factors: teamwork, innovation quality, knowledge learning, and programming practice, which together comprised 21 test items.

3.2.2 Model confirmatory analysis of the second-order factors of innovation ability

It was also necessary to use CFA to further verify whether the revised evaluation index system can reasonably explain innovation ability. If there was a medium-level correlation between the first-order factors and the number of test questions involved was relatively large, there may have been a high-order factor that could explain the relationship among the low-order factors. The second-order factor model is defined as a high-order model that can be generated based on the first-order factor. Marsh and Hocevar[21] believed that the target coefficient is the chi-square value of the first-order factor model or the chi-square value of the second-order factor model. This coefficient can be used as a standard to judge whether the second-order model can dominate the first-order model. If the target coefficient is close to 1, the second-order factor model is more representative than the first-order factor model.

We randomly distributed the revised questionnaires to the research subjects. We distributed a total of 217 copies and obtained 212 valid responses; therefore, the effective response rate was 97.7%. Using the Amos software, we verified that the second-order factor of "innovation ability" constructed by the evaluation index model can be integrated into four first-order factors, which represent team collaboration, innovation literacy, knowledge learning, and programming practice. The correlation analysis results on the first-order factors are as follows: The correlation coefficients between the four factors (0.65, 0.80, 0.60, 0.75, 0.78, and 0.65) show a medium-to-high correlation ($p < 0.001$), and the chi-square value is 201.945. In the second-order factor model, each of the regression coefficients of the second-order factor to the first-order factor is highly strong (0.84, 0.78, 0.95, and 0.69); the chi-square value is 202.676, and the target coefficient is 0.996, which is close to 1. According to Marsh and Hocevar's[21] recommended standards, the second-order factor model can fully express the first-order factor relationship.

3.2.3 Construction and revision of the innovation ability SEM

Regardless of whether the overall structure of the revised evaluation index system was reasonable, we must also use the innovation ability SEM to test whether the EFA result is close to the theoretical analysis of the variable structure and whether the degree of closeness is directly proportional to the validity of the evaluation index system structure. We used the Amos software to construct the initial innovation ability evaluation model on the 212 collected pieces of effective data. We constantly revised the model according to the standard of an MI index value greater than 4. The chi-square value drops to 202.676; the χ^2 degree of freedom ratio (generally required to be between 1 and 3 and inclusive; i.e., the smaller, the better) is 1.388; the absolute fitness index root-mean-square error of approximation = 0.043 < 0.08; the value-added normed-fit index, incremental fit index, Tucker-Lewis index, and comparative-fit index are all greater than 0.9; and the reduced fitness indexes, parsimonious normed-fit index and parsimonious comparative-fit index, are both greater than 0.5. The above indicators reveal that we have reached the adaptation standard required to determine the final model for the evaluation of the innovation ability of postgraduates majoring in computer science (as shown in Fig. 3). Among them, e represents the error value of the second-order factor, represented by e_1, e_2, e_3, etc. And r represents the error value of the first-order factor, represented by r_1, r_2, r_3, etc. That is, the evaluation index system is determined, and the revised questionnaire can be formally used as a portrait data collection source.

4 Construction of the Innovation Ability Portrait Label System

4.1 Basic information label

The basic information label is the basis of the postgraduate

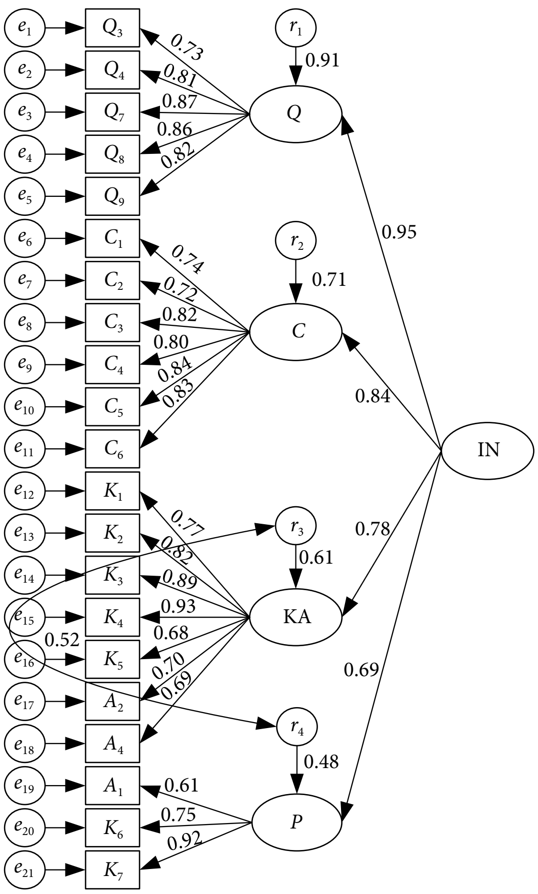

Fig. 3 Final model of the computer science graduates' innovation ability evaluation index system.

students' innovation ability portraits. It is used to describe the basic attributes of postgraduate students majoring in computer science. The label can be directly obtained, including students' grades, majors, and gender, among other information.

4.2 Different dimensions of the innovation ability portrait label

The students' innovation ability portrait model in different dimensions can provide a model framework for constructing the innovation ability portrait and the basic basis for the portrait label library's formation[22]. The division of different innovation ability dimensions is determined according to the evaluation index system's fine-grained division, including the four dimensions, innovation literacy, team collaboration, knowledge learning, and programming practice, as shown in Fig. 4.

4.3 Portrait label of the comprehensive innovation ability level

4.3.1 Determining innovation ability evaluation index weights

The weight coefficient can reflect each index's importance in the evaluation index system. Therefore, whether the index weight is scientifically determined directly influences the innovation ability evaluation level. We normalized the standardized path coefficients of the final model of the innovation ability evaluation index system and obtained each index's weight coefficient. Taking the secondary index of innovation quality as an example, the path coefficients of imaginative thinking (Q_3), innovation motivation (Q_4), self-study ability (Q_7), verbal comprehension (Q_8), and learning comprehension (Q_9) to innovation literacy (Q) are 0.727, 0.813, 0.871, 0.858, and 0.822, respectively. The path coefficients are divided by the sum of the coefficients; thus, we can obtain the weight coefficients of Q_3, Q_4, Q_7, Q_8, and Q_9 to Q. By analogy, the weight coefficients of innovation literacy (Q), team collaboration (C), knowledge learning (KA), and programming practice (P) to innovation ability (IN) are 0.29, 0.26, 0.24, and 0.21, respectively.

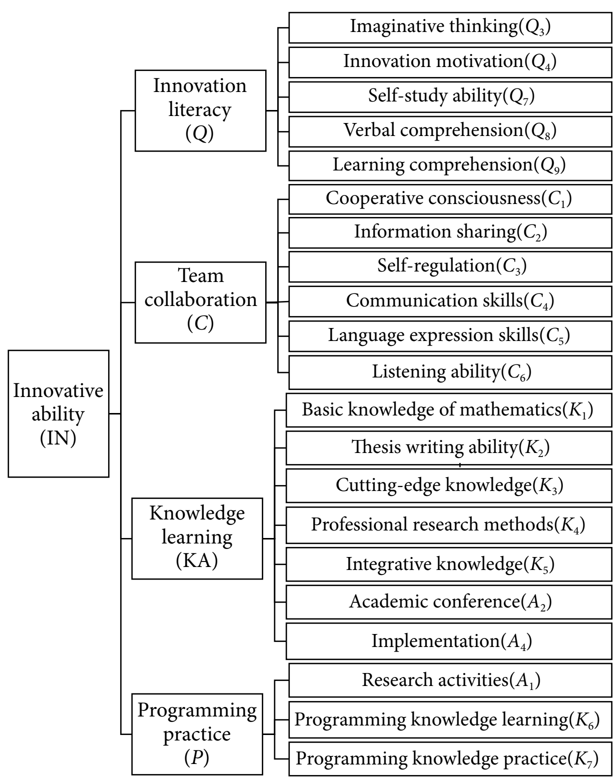

Fig. 4 Different dimensions of the innovation ability portrait label.

4.3.2 Construction of a mathematical model of comprehensive innovation ability-level portrait label

Based on the calculation results of the students' innovation ability portrait model in different dimensions and the corresponding weights, we constructed a mathematical model of the comprehensive level of innovation ability that provides a core framework for the construction of postgraduate students' innovation ability portraits. Following the standardized paradigm constructed by the educational evaluation model[23] according to the importance of Q, C, KA, and P to IN, this research used linear mathematical expressions to quantitatively describe the comprehensive innovation ability level, as shown in the following formula:

$$\begin{cases} \mathrm{IN} = 0.29Q + 0.26C + 0.24\mathrm{KA} + 0.21P, \\ Q = 0.18Q_3 + 0.20Q_4 + 0.21Q_7 + 0.21Q_8 + 0.20Q_9, \\ C = 0.16C_1 + 0.15C_2 + 0.17C_3 + 0.17C_4 + 0.17C_5 + 0.17C_6, \\ \mathrm{KA} = 0.14K_1 + 0.15K_2 + 0.16K_3 + 0.17K_4 + 0.12K_5 + \\ \qquad 0.13A_2 + 0.13A_4, \\ P = 0.33K_6 + 0.40K_7 + 0.27A_1. \end{cases}$$

4.4 Innovation ability group-type portrait label

To divide and portray different student groups, student portrait construction was mainly based on student characteristics[24]. Accurately dividing a group's innovation ability types can aid in understanding the overall level of the current student's innovation ability in the student group to make targeted adjustments and guidance. This k-means clustering algorithm based on the EM was used to cluster groups of students with different innovation ability levels. The optimal clustering number k obtained by the EM algorithm is 3 or 4. After the analysis of multiple factors, we found that when k is 3, the characteristics of innovation ability in different dimensions and the number of student groups are the most appropriate. Then, we performed clustering, and its detailed results are shown in Table 3.

To accurately understand and describe the student groups with characteristics of innovation ability in different dimensions, we used MATLAB R2014a version to visualize the clustering results in the form of a box plot. By comparing the center position and spreading range of the data distribution of each dimension of innovation ability variables in each student group, we obtained three types of student groups, as shown in Fig. 5. According to the characteristics, the innovation ability level of Cluster 1 in all dimensions is significantly higher than those of Clusters 2 and 3, and that of Cluster 3 is significantly higher than that of Cluster 2. Therefore, Clusters 1, 3, and 2 are labeled with high-level innovation ability, intermediate innovation ability, and low-level innovation ability, respectively.

5 Visualization of the Innovation Ability Portrait Label

Combining the labeling system's content with the demand for

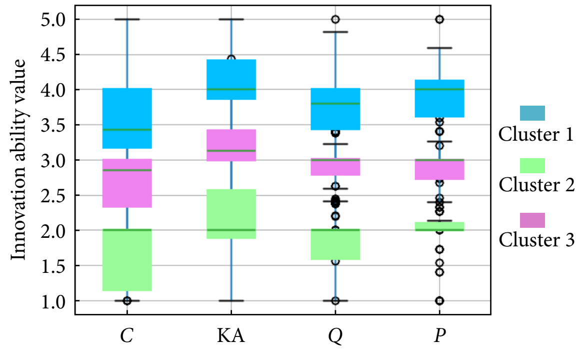

Fig. 5 Comparison of different innovation ability dimensions among groups.

precise portrait applications, this research mainly visualizes students' individual innovation ability portraits and student groups' innovation ability portraits. This approach can help students more intuitively and comprehensively understand their own strengths and weaknesses in all dimensions of innovation ability and carry forward their strengths and compensate for their weaknesses in a targeted manner. Moreover, this approach can help teachers objectively evaluate and understand students' innovation ability performance and adjust guidance strategy and direction accordingly.

5.1 Portrait of students' individual innovation ability

Students' individual innovation ability portraits can help them comprehensively analyze their own innovation ability in different dimensions, improve their sense of self-efficacy, opportunely adjust their individual learning behavior, and improve their innovation ability. We used the visual chart software, namely, ECharts, to portray a portrait of students' individual innovation ability, as shown in Fig. 6. The first three parts of Fig. 6 show students' basic information, the type of innovation ability group to which the students belong, and the comprehensive innovation ability level of the students. This part is the basis for portraying the innovation ability portrait. The rest of Fig. 6 shows not only the students' innovation ability levels in different dimensions but also the average level of all students in each dimension. This part supports students' intuitive understanding and comparison of their own innovation ability levels in different dimensions to adjust their learning behavior in a targeted manner and improve their innovation ability.

5.2 Students' group innovation ability portraits

Students' group innovation ability portraits can help teachers adjust their teaching strategies according to the group distributions of students' innovation ability at various levels to significantly improve all students' innovation ability levels. In addition, these portraits can help teachers provide timely and targeted guidance and intervention according to students' varying innovation ability levels in various dimensions to recommend personalized educational resources. Therefore, the portraits

Table 3 Clustering results of the student groups with different innovation ability levels.

Cluster student group	Number of students	Proportion of students (%)	Ability value			
			Innovation literacy (Q)	Team collaboration (C)	Knowledge learning (KA)	Programming practice (P)
Cluster 1	22	10.5	3.665	3.592	4.120	3.918
Cluster 2	46	22.0	1.814	1.682	2.153	1.977
Cluster 3	141	67.5	2.920	2.668	3.254	2.904

	Basic information					
	QQ	11******21	Sex	Male	Grade	2
	Major	Computer science and technology	Major type	Academic postgraduate	…	
Group types of innovation ability			Comprehensive level of innovation ability (total score: 5)			
High-level innovation ability			3.6675			
Average innovation ability level for all dimensions			Different dimensions of innovation ability			

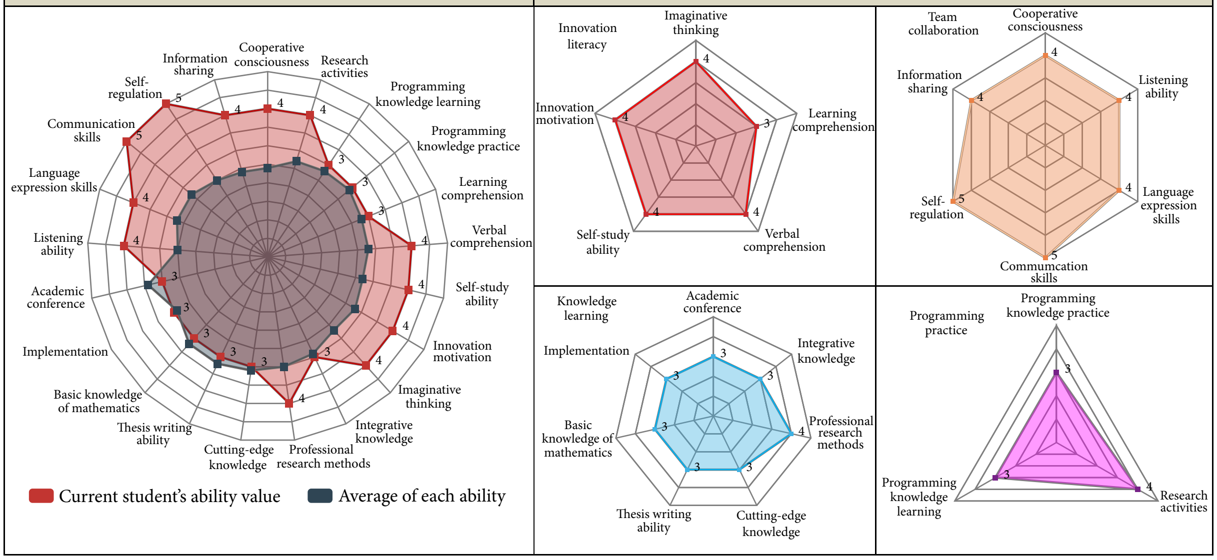

Fig. 6 Students' individual innovation ability portraits.

include statistics on the students' group portraits with different innovation ability levels and students' individual innovation ability portraits, as shown in Fig. 7.

6 Intelligent Application of Innovation Ability Portraits

This portrait technology for evaluating postgraduate students' innovation ability can accurately identify students' actual innovation ability levels in various dimensions, comprehensively address the advantages and disadvantages of their innovation abilities, and deeply dig into their personalized needs. This technology can be applied to different intelligence education scenarios, such as students' personalized learning, teachers' accurate teaching, and schools' intelligent educational decision-making. Through the postgraduate students' innovation ability portraits, we can use technologies, such as recommendations and knowledge maps, to customize learning content and plan student learning paths to establish personalized learning. This technology also recommends teaching content and mode for teachers to optimize teaching design. Artificial intelligence can provide early

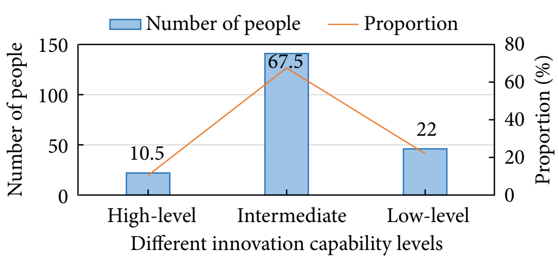

Fig. 7 Display of students' group innovation ability portraits.

warnings regarding students' abnormal performance, allowing the development trend of students' innovation ability to be opportunely predicted to adjust learning behaviors. Through innovation ability portraits, universities can improve their talent training programs, reform enrollment and selection methods, and optimize library resource allocation.

Taking resource recommendations as an example, we adopted a computing model of crowd intelligence computing and designed and implemented a personalized recommendation system for educational resources based on an innovation ability portrait. The crowd intelligence computing system comprises a user and a platform. The user completes the perception task using a mobile device as the perception source, while the platform comprises many servers, which are responsible for information collection and data storage, among other tasks[25]. After the user constructs an innovation capability portrait using the mobile device, the platform adopts the decentralized distributed computing mode, divides the user demand tasks into small independent tasks, and computes them in parallel on different servers to identify the most appropriate educational resources for the user at an optimal rate for optimizing the recommendation efficiency.

The system includes an ability analysis and testing module, an education resource database, and a personal center module. The ability analysis and testing module collects data through the entry of basic information and questionnaire answers, and the back end conducts an ability analysis and portrait visualization according to the constructed portrait label system. The education resource database module divides and stores the education resource data according to the innovation ability category, and the user finds detailed information on demand resources through the search box. The personal center module displays the user innovation ability analysis results, the innovation ability portraits, and personalized educational resource recommendations. A part of the implementation interface is shown in Fig. 8.

The system is implemented using the WeChat Development Tool (1.05.2102010). The system's front end uses JavaScript, WXML, WXSS, and other languages for compiling, and the system's back end uses WeChat cloud development technology to implement the design structure. Moreover, the system uses white-box testing to evaluate functions, such as login authorization, updating, question answering, and information entry. Furthermore, we interviewed 32 computer postgraduates who used the system to obtain their feedback on the recommendation results of the system, and the satisfaction rate was 84.4%. These results demonstrate that the system can promote the personalized cultivation of students' innovative abilities.

7 Conclusion and Outlook

In this artificial intelligence era, innovation intelligence computing is a hot topic in cultural computing, and innovation ability portrait technology is a way to achieve it. The designed portrait label system is the key to accurate portrait construction and provides the basis for the realization of personalized innovation ability cultivation. In this research, we used the innovation ability evaluation index system, combined with the qualitative and quantitative analysis and construction process of the evaluation indicators, as the theoretical guidance for the portrait label system's design. Then, we used clustering and factor analysis to design the innovation ability portrait label system. The labels were represented as students' individual innovation ability and student groups' innovation ability portraits. The portraits were used in the educational resource recommendation system for the innovation ability portrait of computer majors, effectively improving the personalized training of postgraduate students' innovation ability and intelligently realizing the core value of university innovation culture. In the next step of this research, we will combine the innovation ability portrait with the knowledge map technology planning learning path to improve the personalized training effect of computer graduates' innovation ability.

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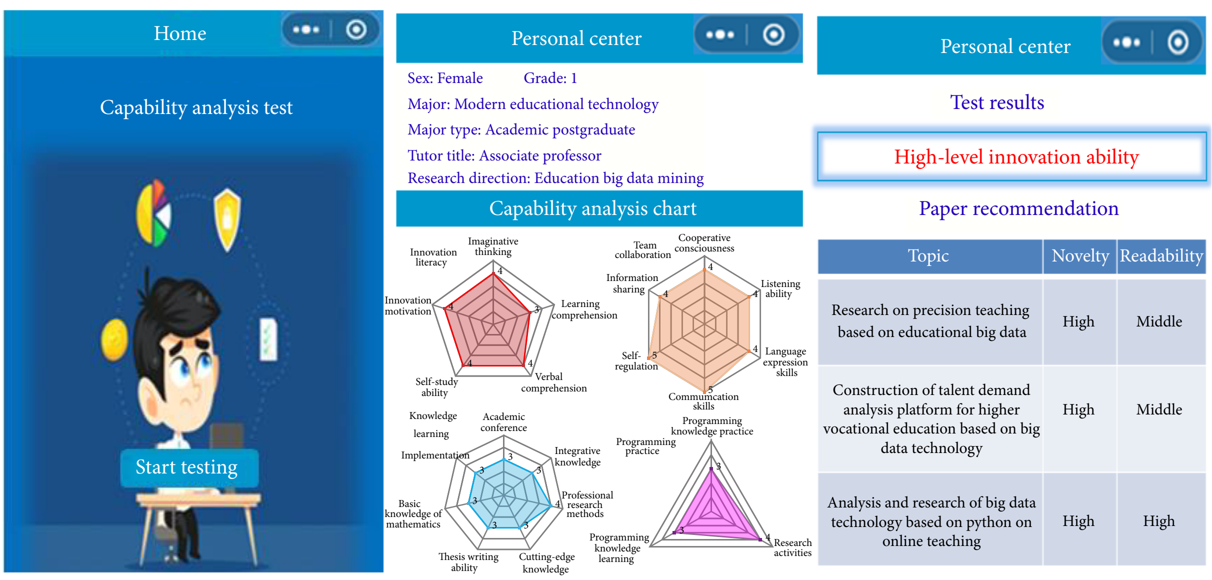

(a) System home page (b) Ability analysis (c) Recommendation result

Fig. 8 Personalized recommendation system for educational resources based on innovation ability portraits.

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