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Construction of a cross-disciplinary talent cultivation platform for rural revitalization driven by deep reinforcement learning algorithms: The case of Ningbo Future Rural College

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Abstract In the era of digital economy, the rural revitalization strategy has an urgent demand for composite talents, but the existing talent training mode is difficult to accurately match the industrial demand. The traditional cultivation method lacks in-depth analysis of the multidimensional characteristics of talents, and the construction of interdisciplinary cultivation platform is lagging behind. This study builds an interdisciplinary platform for rural revitalization talent cultivation based on big data analysis and multiple intelligence theory. TF-IDF algorithm and K-means clustering analysis are used to data mine 30 job samples from five major recruitment platforms to establish a talent portrait model with a two-dimensional multi-level labeling system. Through genetic optimization FCM algorithm for clustering analysis, the rural revitalization talents are classified into three types of prototypes: professional and technical, operation and management, and local return type. Develop an interdisciplinary digital learning platform based on ASP.NET Core framework to realize the functions of talent demand display, skill learning and data visualization. Taking 345 students of Ningbo Future Country College as the survey object, a five-level Likert scale was used to assess the effect of the platform. The results show that the questionnaire reliability coefficient of 0.884 and the KMO value of 0.904 meet high standards, 46.96% of the students are satisfied with the teacher interaction, 43.48% think that the course content is streamlined and efficient, and 40.87% say that they can absorb more than 75% of the lecture content. The study provides a theoretical basis and practical path for the precise cultivation of rural revitalization talents.

Index Terms Digital Economy, Rural Revitalization, Talent Portrait, Multiple Intelligences Theory, Interdisciplinary Platform, Big Data Analysis

I. Introduction

Since the implementation of rural revitalization strategy, the countryside has ushered in the best development time [1]. Talent cultivation and teaching mode related to rural revitalization have also become one of the hot topics of recent higher education teaching reform [2]. Talent training for rural revitalization is the primary path for colleges and universities to serve rural revitalization, and in the process of rural revitalization talent training, the value orientation, research object, teaching practice activities and rural development needs are combined, not only to achieve the multi-dimensional direction of education and teaching services for rural revitalization [3], [4]. It also practices “writing papers on the motherland” and ensures the comprehensive promotion of “rural revitalization strategy” [5].

Interdisciplinary personnel training is of great value and significance in promoting the cross-disciplinary integration and promoting the development of science and technology, as well as meeting the students' interest in interdisciplinary learning and cultivating composite talents needed by the society, which makes it an important content and direction of the current reform of higher education [6], [7]. We want to promote interdisciplinary talent training by using the “catalyst” of interdisciplinary cross-fertilization, we need to fully “break the barriers of disciplinary specialties”, and establish a sound mechanism for the training of interdisciplinary talents [8]-[10]. The so-called interdisciplinary personnel training mechanism is to ensure the smooth implementation of interdisciplinary personnel training, smooth operation, continuous development of the unity of institutions and systems, but also to promote interdisciplinary personnel training as a supportive condition for rural revitalization [11]-[13].

With the rapid development of digital economy and the in-depth promotion of rural revitalization strategy, the transformation and upgrading of rural industrial structure has an increasing demand for compound talents. There are obvious shortcomings in the current rural talent cultivation system: the cultivation mode is single, which is difficult to adapt to the requirements of industrial integration and development, the cultivation content is out of touch with the actual demand, and there is a lack of accurate talent demand analysis, the interdisciplinary cultivation mechanism is incomplete, which restricts the effect of composite talent cultivation. The traditional way of talent cultivation relies more on empirical judgment and lacks the support of data-driven scientific decision-making. In this context, how to use big data technology to accurately identify the characteristics of talent demand for rural revitalization and build an interdisciplinary training platform adapted to the development of the digital economy has become an important issue in promoting the comprehensive revitalization of the countryside. Based on this, this study proposes to combine big data talent portrait technology with multiple intelligence theory, design and develop an interdisciplinary digital cultivation platform by mining the talent demand characteristics in recruitment big data to provide talent support for the rural revitalization strategy. Firstly, to construct a label generation method for talent portrait based on big data, adopt TF-IDF algorithm to extract keywords, use K-means clustering technology to deeply mine recruitment data, and establish a two-dimensional label system covering basic attributes and specific attributes, secondly, to conduct clustering analysis of talent prototypes through genetic optimization FCM algorithm to identify the core features of different types of talents for rural revitalization, and to form a accurate talent portrait, finally, based on the results of talent portrait analysis, design and develop an interdisciplinary digital cultivation platform, and conduct an empirical study with Ningbo Future Rural College as an example to verify the practical application effect of the platform.

II. Big data-based label generation method for rural revitalization talent portrait

This chapter proposes a talent portrait label generation method based on big data, which is applied to the characterization of outstanding talents in the field of rural revitalization to provide a basis for the design of an interdisciplinary platform for rural revitalization talent cultivation.

II. A. Talent Profiling Technology Based on Big Data

Talent portrait technology based on big data can help enterprises discover the matching relationship between talent traits and job requirements, and provide better suggestions for talents and enterprises. Taking the talent portrait data as a basis, it constructs a dynamic hierarchical segmentation adjustment system, improves the talent cultivation objectives, gives full play to the real data, and improves the quality and effect of rural revitalization talent cultivation.

II. A. 1) Basis of Talent Profiling Data Analysis

The main basis of the talent portrait technology is a two-layer data warehousing design, the first layer of the original data collection and pre-processing, through the talent data background, network access to collect data and complete the summary, the collection of data for cleaning and processing, the redundant data will be deleted. The second layer is the analysis results, mainly responsible for saving the label after data integration and constructing the talent portrait. Among them, the label can be designed into two parts: content and weight, the content of the label extracted from the talent is not always unchanged, and its weight changes over time. The use of labels can be used to propose a targeted selection program for the talent.

II. A. 2) Talent Portrait Data Information Acquisition and Preprocessing

In the big data environment, there is a lot of talent data information that can be mined, and data analysis technology should be utilized to collect talent user characteristic identification data, and the main data information identification of talent portrait is shown in Figure 1.

(1) User level. Talent user level mainly includes middle and high-end talents, white-collar talents, blue-collar talents and fresh graduates.

(2) Geographical distribution. Based on the regional distribution of network talents, it shows the job-seeking needs of talent users of various age groups in different regions of the country, and facilitates the provision of accurate information for enterprise recruitment.

(3) Talent qualifications. Talent qualifications are also labels such as education, major, and graduation school.

(4) Gender. It is also known as the male and female gender labels, the use of sending electronic resumes on. Male and female talents to determine the preference of each occupation.

(5) Behavioral characteristics. Behavioral characteristics, which is also known as the number of times the talent clicked on the job application in the job site label, can be based on the talent browsing behavior and user activity to obtain.

(6) Social network. Social network is also through the registration and login social network and enterprise platform label.

(7) Professional skills. Professional skills is the talent in the field in which the credentials can reflect their own ability, including qualifications, patents and so on.

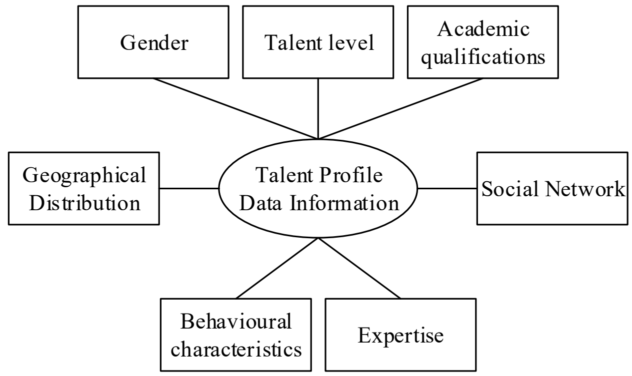

Figure 1: Talent profile data information

There are many redundant, repetitive and erroneous data in the collected data, in order to improve the accuracy of the data and prevent the negative impact on the label mining and decision making, the collected raw data should be cleaned and processed by data analysis algorithms to prevent the redundant labels from interfering with the mining operation.

II. B. Overall Construction Process of Talent Portrait Model

This paper analogizes the characteristics of talent demand in the field of rural revitalization to the archetypes of each comprehensive character in the user portrait, and constructs a labeled talent portrait model from multiple perspectives of the research object, portrait goal, model elements, research methodology, and presentation form.

II. B. 1) Talent portrait model construction process

Talent image construction based on recruitment data is essentially the process of data → labeling → visualization of talent demand, talent image model construction process shown in Figure 2, which can be roughly divided into data collection and processing, building talent image model and talent demand characteristics mining.

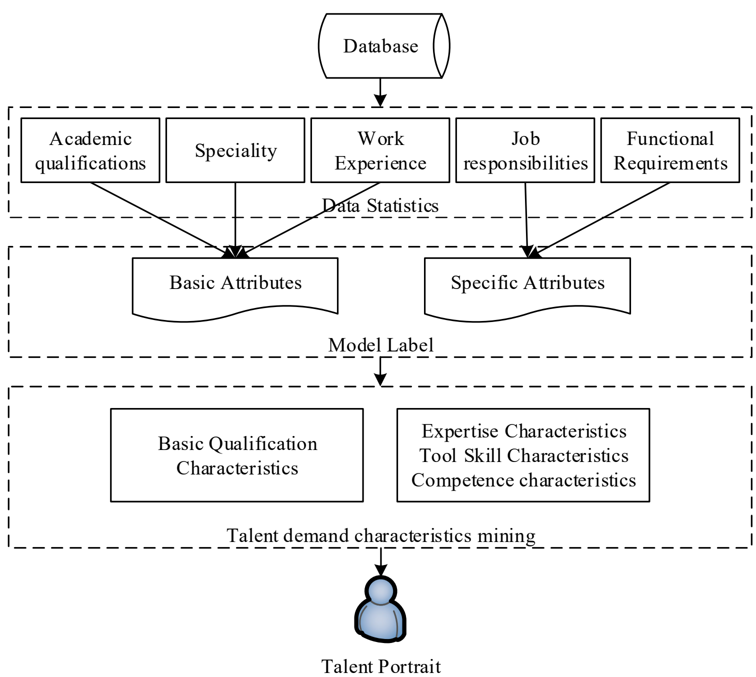

Figure 2: The construction process of the talent portrait model

The specific steps of talent portrait model construction are:

Step 1: Data collection and processing. Take the influential recruitment platform as the data source, obtain the text of work experience, education, job duties and job requirements in each recruitment information with the help of web crawler, and perform operations such as character filtering, text segmentation and deactivation to form an effective talent portrait data set.

Step 2: Subdivide the composition dimensions of the portrait and build a talent portrait model. Starting from the basic attributes and specific attributes, we construct a two-dimensional multi-level labeling system of talent portrait model. The basic attributes are the explicit job descriptions of the enterprise demand, including the education, specialty and work experience of the talent. Specific attributes are the specific deep performance of the talent demand information and the invisible inner potential to be tapped, including professional knowledge, tool skills and ability quality.

Step 3: Talent demand feature mining. Reconstructing a comprehensive and accurate dictionary is the key to successfully mining the characteristics of talent demand, but it is difficult to extract and identify professional terms using the existing dictionaries of common dictionaries and Jieba library, so 500 job information samples are randomly selected for keyword extraction, high-frequency word screening, and semantic approximation of word additions in order to construct a relatively complete recruitment dictionary of professional fields.

II. B. 2) Talent demand characteristic mining process

Talent demand feature mining process is shown in Figure 3, the specific process is as follows:

(1) Keyword extraction. Use TF-IDF keyword extraction algorithm [14] to calculate the weight of the feature words, extract the keywords of recruitment information and statistical analysis, screening the words that reach more than 200 frequency.

(2) Semantic approximation addition. With the help of Word2Vec open-source tool to screen “top200” high-frequency words in the semantic approximation of words, after manual screening, the final dictionary contains 384 words. Finally, from the perspective of basic qualifications, professional knowledge, tools, skills and abilities to build a talent portrait labeling system to present the job characteristics of talent demand information.

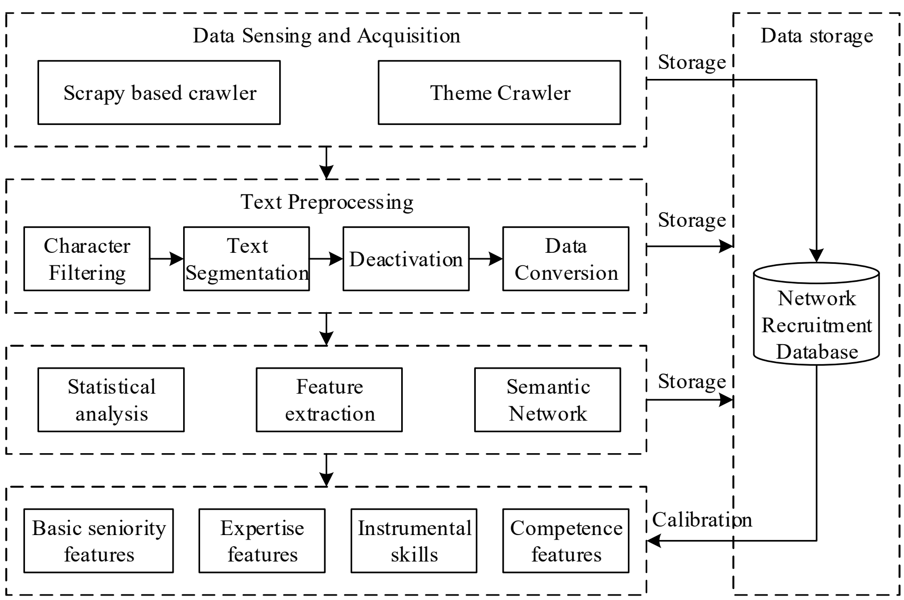

Figure 3: The process of mining the characteristics of talent demand

II. C. Specific construction method of talent user profile

II. C. 1) Talent Profiling Model

(1) Data standardization. The construction of talent portrait should analyze the ability of resource integration in different media, and construct a unified standard to realize the construction of a complete talent portrait.

(2) Talent information integration. Talent information is statistically analyzed, main factors are extracted, and the raw data collected are cleaned and processed through data analysis algorithms. The theme web crawler is designed through the similarity of job content and theme, and the theme is expressed through word or phrase feature words, and the content can also be divided into words and phrases, so as to describe the theme and web page through the vector space model. In order to form a feature vector describing the topic, a number of web pages related to the topic are keyword extracted, and then the feature vector and vector weight of the topic can be obtained. Through the vector space model, the content can be described as a word frequency vector as in equation (1):

$$C_{TF} = (TF_1, TF_2, \cdots, TF_n) \tag{1}$$

where, TF_i denotes the frequency of words describing the i nd content in the website.

In this paper, the relevance of the website is measured by the cosine interval [15], in the case where the angle of pinch is $0°$, the similarity is highest at 1, which means that the content and the topic are most relevant. Conversely, in the case where the angle is $90°$, the similarity is lowest at 0, which means that the web content and the topic are not relevant. The similarity is calculated as in equation (2):

$$Sim_{(t,s)} = \frac{\sum_{k \in t \cap s}^{n} \omega_{tk} \times \omega_{sk}}{\sqrt{\sum_{k \in t}^{n} \omega_{tk}^2} \cdot \sqrt{\sum_{k \in s}^{n} \omega_{sk}^2}} \tag{2}$$

In the formula, t denotes the collection of words describing the embodied theme, s denotes the collection of linked texts describing the theme, ω_{tk} denotes the relevance of the feature words in the collection of descriptions, and ω_{sk} denotes the criticality of the feature words in the collection of descriptions with respect to a certain theme, and the specific calculations are shown in Equation (3):

$$\omega_{tk} = TF_{tk} \times IDF_{tk} = \frac{TF_{tk}}{\sum_{i=1}^{n} TF_{ts}} \times \log\left(\frac{N}{nk}\right) \tag{3}$$

where, TF_{tk} denotes the frequency of occurrence of the description topic, N denotes the number of all documents in the description document set, and nk denotes the number of documents in which the description appears.

Through the crawler cleaning processing of the recruitment website, the content is analyzed, through the formula (1), formula (2) to find out the theme similarity, the results obtained compared with the established threshold, if the similarity exceeds the threshold, then the content is considered to be related to the theme, the need for content extraction.

(3) Label mining. Processing and processing of labels using the deployment environment platform, completing structured operations for crawled data, and data mining through cluster analysis methods.

In this section, the K-means algorithm [16] is selected, whose clustering objective is to divide the sample points into several clusters using clustering based on the clustering chengdu in the given number of groupings $k(k \le n)$. In the same clusters, the data similarity is very high, but the similarity between the clusters is very low. That is, for the set of clusters $A = \{A_1, A_2, \cdots, A_k\}$, the minimum value is calculated in the numerical model for the following equation, where μ_i is used to describe the mean value of the classification A_i, as in equation (4):

$$\overline{A}_i = \min \sum_{i=1}^{k} \mu_i^2 \tag{4}$$

The detailed process is as follows:

Step1: For n talent data object collected, treat k objects as initial clustering centers.

Step2: Find out the degree of difference between each object and the above center according to the mean value of each clustered object, and classify the above elements in order to the cluster with the lowest degree of difference.

Step3: Recalculate all the changed cluster means.

Step4: Repeat running Step2 and Step3 until all clusters do not appear to change.

Step5: Output the results.

The talent attributes are composed into records to get the set $(x_1, x_2, \cdots, x_n)$ with n data record, while all x_i are d dimensional vectors, that is $x_i(x_{i1}, x_{i2}, \cdots, x_{id})$, where $x_{i1} - x_{id}$ represents the talent label.

The cleaned data is mined by K-means algorithm, and the same kind of data is gathered together to mine the talent labels. At this point, the talent portrait technology application visualization model construction is completed.

(4) Label verification. Utilize actual cases to verify the accuracy of the mining label results, so that the processing results corresponding to the label reach the expected results.

II. C. 2) Precautions for Talent Portrait Application

(1) Combining business. The actual business scenario or the field to which it belongs needs to be taken into account in the process of establishing the talent portrait to prevent it from being too abstract, and the names of the labels in the same environment have different meanings to a large extent and should be treated separately.

(2) Control granularity. Portrait granularity is not the finer the better, the split label is not the more the better, the more the number of split labels, the fewer the number of people covered, the worse the description performance, the more likely to be pseudo-features.

(3) Dynamic change. Can not blindly adopt the talent portrait, the vast majority of talent portrait is a static feature, talent characteristics will change with the change of time and space, there are certain dynamic talent portrait information, such as talent in the recruitment website access path and time.

II. D.Optimized Design for Talent Label Generation

This section optimizes the design of the talent label generation process in the construction of the talent portrait to further improve the accuracy of the talent portrait and lay the foundation for the cultivation of rural revitalization talents.

II. D. 1) Talent Labeling System Convergence Model

Based on the results of talent tag big data mining and attribute feature extraction, the edge profile feature extraction and pixel fusion methods of user image are used to obtain the equivalent feature components of talent tag node k :

$$\hat{Y} = \frac{\int_{-\infty}^{\infty} y f_k(x,y)dy}{\int_{-\infty}^{\infty} p_i(x,y)dy} \tag{5}$$

where f_k denotes a multi-label seed node, p_i denotes the set of association distributions indicative of a three-level labeling system. By transforming the base labels through the split-box component for feature engineering, the talent label attribute quantization level optimization problem is obtained under the cognitive cooperation model which can be expressed as:

$$F_i = \frac{(1+S_i^2)\Gamma}{\mu_{ik}^2 \hat{Y} - y} \tag{6}$$

where $\Gamma = \frac{-\ln(5B_k)}{1.5}$ represents the output feature quantity encoded by the user through the three-level labeling system, and B_k represents the matching feature quantity of talent construction demand combined with specific business scenarios.

Adopting the two-by-two planning model, we construct the fuzzy correlation index distribution set for talent resource label identification, and get the fusion relationship of talent resource labels as:

$$E = \frac{y-\hat{Y}}{F} \tag{7}$$

The fusion relationship model under the global optimal talent constraints is obtained by applying the user profile support technique to each sub-talent attribute as:

$$M_i = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{F_i - \hat{Y}_i}{E}\right)^2 \tag{8}$$

According to the construction and application system model of the talent label system, the basic label recognition method is adopted, combined with split-box component detection, to realize the label information fusion and the edge profile feature detection of the human figure, so as to realize the recognition and optimization of the construction of the talent labels of the specific business scenarios.

II. D. 2) Talent Labeling Big Data Clustering and Business Scenario Matching

Design the assignment system and aggregation rules of the basic label in line with the talent resource management, based on the results of talent label recognition in different business scenarios, combined with expert models and machine learning methods, the association rule clustering function is obtained as:

$$Z = \prod_{i=1}^{n} \frac{E+\eta_{ik}}{\sum_{k=1}^{c}(y-\mu_{ik})} \tag{9}$$

Higher-order label prediction method is used to analyze the fuzzy correlation factors of talent resource management, and analyze the correlation attribute feature components of talent labels to get the label and weight distribution information as:

$$U = \lim_{n \to \infty} \frac{1}{n} E\left\{ \sum_{k=1}^{c} \int_0^{\infty} a_{ik} \cdot f(x,y) dx \right\} \tag{10}$$

The base label will be feature transformed to extract the feature commonality of the same type of talent through the split-box component, and the uploaded label information clustering matching result can be obtained as:

$$L = \sum_{k=1}^{c} \rho_k \log_2 \left(1 + \frac{|v_{ik}|^2 Z}{\sum_{k=1}^{c} |\eta_{ik}|^2 M_i + \Gamma \sigma^2} \right) - U \tag{11}$$

where ρ_k is the amount of detection statistics features. The results of talent resource big data fusion clustering analysis are obtained as:

$$p_{k,n} = \left[\Delta_{k,n} - \frac{\sum_{k=1}^{c} |L|^2 \beta_{k,n} + \Gamma \sigma^2}{|\mu_{ik}|^2} \right]^* \tag{12}$$

Among them:

$$\Delta_{k,n} = \frac{p_i}{\ln 2} \left(\frac{|U|^2}{B_k} + \frac{\Gamma \sigma^2}{|Z|^2 B_k} \right) \tag{13}$$

According to the above analysis, the base label is transformed to extract the feature commonality of the same type of talent through the feature engineering transformation of the split-box component to realize the optimized design of talent label generation.

III. Case analysis and application

In order to verify the effectiveness of the proposed talent portrait label generation method, this chapter applies the method to conduct a case study, taking the main recruitment platforms in the integrated recruitment and vertical recruitment modes as the data source, collecting data from the five major recruitment platforms, and mining the talent demand in the field of rural revitalization through the construction of talent portraits.

III. A. Recruitment data collection and analysis

The pre-processed recruitment information as a document, the text word N-base is obtained as a condition after the split-word marking, and nearly 146 topic sub-words are analyzed by using R language programming and screened and analyzed again.

In this paper, five experts were invited to evaluate the effectiveness of these subject participles in combination with the related job posting text sentences and calculate the corresponding weight values. Each participle effectiveness assessment options are divided into five levels: invalid, somewhat effective, effective, very effective and extremely effective, and were assigned the value of 1, 2, 3, 4, 5. Experts were evaluated separately after the evaluation of each participle will be derived from the five levels of evaluation ratio, select “effective” and the above statistics, to 67% as the limit. If the total percentage of “effective”, “very effective” and “extremely effective” is less than 67%, then the deletion of the sub-phrase is considered invalid.

By calculating the weight of each participle, the participle with the top 100 weight value is selected as the demand attribute word, and the partial data of the demand attribute word is shown in Table 1.

Table 1: Partial data of requirement attribute words

Summary of key words	Weight value	Effectiveness rating /%					Effective and above /%
		Invalid	Slightly effective	Effective	Very effective	Extremely effective	
Agricultural technology	0.0148	0	18%	22%	36%	24%	82%
Rural culture tourism	0.0145	18%	0	38%	22%	22%	82%
Ecological protection	0.0142	0	18%	0	40%	42%	82%
Basic governance and planning	0.0140	0	18%	18%	25%	39%	82%
…	…	…	…	…	…	…	…

III. B. Talent Attribute Scale

By analyzing the high-frequency demand attribute words obtained in text data mining, these talent demand attribute words can be used as the primary attribute and secondary attribute related labels of the talent portrait attributes, which are used as the dimensional conditions for constructing the talent portrait.The 5W2H method is a further deepening and development of the situational analysis method, and the basic framework of the product can be constructed by summarizing the basic influencing factors. Based on the role of the 5W2H method for the design of the talent attribute scale, in which the scale is mainly divided into two parts, the first part of the recruitment data is subdivided into 10 categories, objectively record the job requirements in the recruitment position and the frequency of each category. The second part defines five influencing factors to obtain the deep-seated talent demand and recruitment motivation of the recruitment position. Based on the type distinction of subject words in Table 1, 5 demand attribute words with high word frequency ranking are selected as attribute factors under each influence factor respectively, and assigned values 0 and 1.

III. C. Cluster analysis and results

In the attribute clustering analysis stage of talent profiling, the theory of fuzzy clustering uses matlab data processing tool for attribute factor clustering analysis. The number of clusters is 3-6 when the study found that it will be easy to handle and communicate. During the research process by communicating with the business side, the number of clustering categories was set c=3. The partial data of the clustering center matrix of the prototype clustering of 3 categories was calculated by genetic optimization FCM algorithm to obtain the clustering center matrix of the prototype clustering of 3 categories is shown in Table 2.

Table 2: Partial data of cluster prototype matrix center

Factor sequence number	1	2	4	11	12	15	16	17	21	24	26	27	29	32	35
Cluster 1	3.11	1.36	0.35	0.57	0.52	0.61	0.66	0.68	0.56	0.81	0.51	0.4	0.65	0.71	0.73
Cluster 2	2.51	1.68	0.85	0.48	0.55	1.04	0.57	0.4	0.63	0.61	0.34	0.32	0.57	0.45	0.38
Cluster 3	3.53	1.89	0.72	0.59	0.38	0.73	0.38	0.34	0.79	0.49	0.37	0.43	0.63	0.49	0.25

Operate the fitness function, perform the selection, crossover, and mutation operation steps, and retain the individuals with high fitness to form the next generation, and the results of the fitness curve are shown in Fig. 4, from which it can be seen that the fitness tends to be optimal at the beginning after an average of 40 iterations, and terminates the operation after 120 iterations.

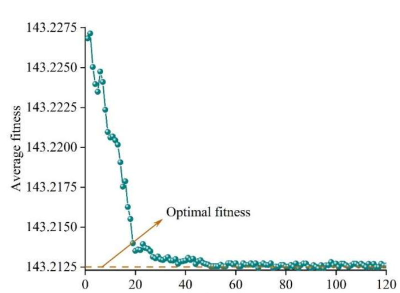

Figure 4: Fitness curve

The 30 job samples are grouped according to the object of maximum affiliation, and the sum of the affiliation of each sample to the 3 clustering archetypes is 1. The final clustering dendrogram is shown in Fig. 5. From the dendrogram, it can be seen that there is a high degree of similarity in the internal zones of the clusters, and there is a significant difference between the clusters. The distribution map of the 3 clustering prototypes as well as their corresponding feature attributes are shown in Table 3.

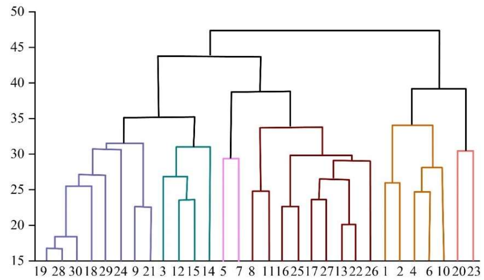

Figure 5: Tree diagram of the prototype of type 3 clustering

Table 3: Three types of clustering prototype distribution

Clustering prototype	User sample
Clustering prototype 1	19,28,30,18,29,24,9,21,3,12,15,14
Clustering prototype 2	5,7,8,11,16,25,17,27,13,22,26
Clustering prototype 3	1,2,4,6,10,20,23

III. D. Talent Profile Creation

In order to make the talent portrait more vivid, talent attribute labeling is not enough, the creation of talent portrait should be closer to digging the motivation behind the hiring needs. In order to get valuable and deep insights into job recruitment needs. The three types of talent prototypes analyzed through quantitative research as a reference, and 30 samples and three types of prototypes and the closest samples 1, 5, 19, 2, 7, 28 of a total of six recruitment samples for in-depth interviews, and ultimately obtain three types of talent portrait, respectively, professional and technical, operation and management, and the local and returnee type. In terms of talent positioning, professional and technical talents have technical ability in agriculture, science and technology, ecology, culture and tourism and other professional fields, which is the core driving force for rural revitalization. Operation and management talents have the ability of resource integration, project management and operation, and are the organizers and promoters of rural revitalization. Local and returning talents are familiar with rural culture and environment, and are the bridge connecting external resources and local environment. In terms of demand scenarios, professional and technical talents are mainly suitable for industrial revitalization and technological upgrading, while operation and management talents are in demand for industrial operation and organizational management. Local and returning talents are applicable to the fields of cultural inheritance and local industry activation.

IV. Design of an interdisciplinary digital platform for the training of rural revitalization talents

On the basis of mining the talent cultivation needs in the field of rural revitalization using talent portrait technology, this chapter designs an interdisciplinary digital platform for rural revitalization talent cultivation.

IV. A. Functional analysis and design of the platform system

This platform is a Web-based application, designed and constructed with the goal of implementing the rural revitalization strategy as a foothold, and serves as an interdisciplinary learning platform to help cultivate professional talents for rural revitalization. The platform system is divided into four types of role users, and is intended to realize the display of talent demand information and professional skills learning functions, mainly providing the rural industry job demand information query, rural entrepreneurship help and data visualization services. The platform focuses on the user's visual experience, adding an originally designed Logo logo in the learning section, which can show the career characteristics and prospects, and play a role in expressing and helping learning on the visual level. The platform's unified page design and page layout with green as the main color reminds people of the theme tone of environmental protection, green and ecology, with a sense of friendliness. The platform values the user's operating experience and optimizes the page design on the basis of realizing the basic functions, reflecting the ease of use and practicality of the project. The functional structure design of the platform system is shown in Figure 6.

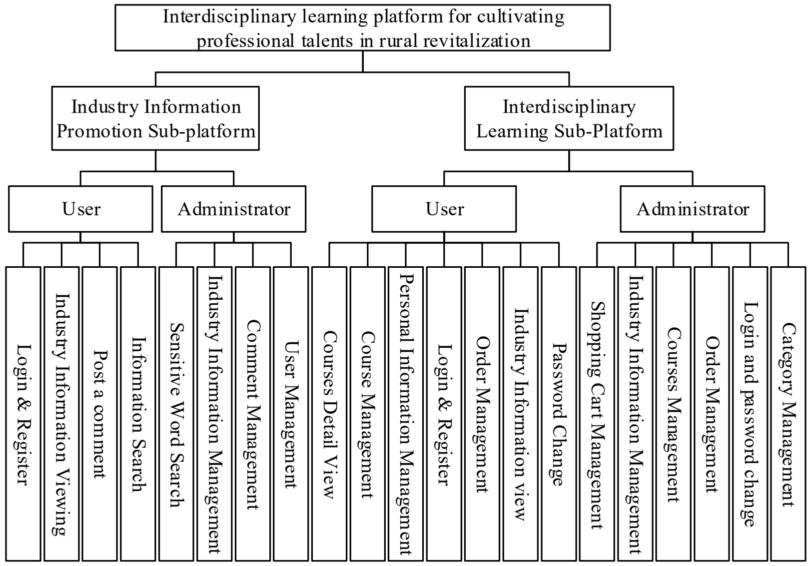

Figure 6: System Functional Structure

IV. B. Platform system implementation

The development of this platform is dedicated to assisting the rural revitalization policy and is based on the development framework of ASP. NET Core Web using C# language and MVC design pattern. The front-end and back-end coding of the sub-modules of this platform uses Visual Studio 2019 and 2022 versions respectively, and SQL Server 2008 is used to store and manage the data of relevant information. The databases are named Webdb and Modelwz, Webdb is used to store the interdisciplinary learning module and Modelwz is used to store the industry information module, in which the data for data visualization is stored in Modelwz, including indicators such as gross regional product of each prefecture-level city, total power of agricultural machinery, and the rate of harmless treatment of domestic waste. Using ThreeLayer structure, the basic statement for connecting to the database is encapsulated in the DAL layer, the logic processing of the business is put in the BLL layer, and the interface shown to the user is put in the UI layer, which the user can't access directly, but access the corresponding view.

This system designs the user interface in accordance with the actual operation of talent management and the needs of rural revitalization talent cultivation, which can meet the various needs of learning the vocational skills related to rural revitalization and job recruitment.

IV. C. Survey study on quantitative analysis of the effectiveness of the platform's delivery of lessons

This section takes Ningbo Future Rural College as an example to explore the practical effects of the designed platform in the cultivation of interdisciplinary talents for rural revitalization.

IV. C. 1) Background, target audience and methodology of the survey

(1) Background of the survey

The purpose of this survey is to try to dig out the ways and means to improve the effectiveness of interdisciplinary talent training for rural revitalization by means of a web-based questionnaire in order to make further improvements to the platform.

(2) Survey Objects

The survey object mainly involves 345 freshmen, sophomores and juniors in Ningbo Future Country College.

(3) Survey Methods

1) Questionnaire survey method. Network questionnaire survey method is widely used in social surveys at home and abroad. The questionnaire was set up with 12 questions, 11 single-choice questions and 1 multiple-choice question. Mainly through the Likert five-level scale to start the network questionnaire survey, its advantage is that each student operation standardization, answer convenient, answer results can be directly exported through the questionnaire network, 0 cost.

2) Statistical analysis method. In the age of informationization, the promotion and application of electronic computers have created conditions for the distribution of questionnaires. The development of science and technology is rapidly changing and becoming more and more quantitative, quantitative research has become the trend of teaching reform research.

IV. C. 2) Reliability and validity of the survey

(1) Reliability analysis

The main measure of reliability analysis of this questionnaire is Cronbach's Alpha coefficient. This study is mainly analyzed by SPSS28.0, and the reliability analysis of the platform lecture effect survey is shown in Table 4, and the data after the questionnaire reliability is deleted or corrected is shown in Table 5. Among them, question items 1~8 are classroom atmosphere of online class is better than offline (Q1), teacher interaction on online class is more than offline (Q2), content on online class is streamlined and learning efficiency is high (Q3), online class won't be late (Q4), teacher of online class prepares the class more carefully (Q5), it is more convenient for online class to take notes (Q6), after the lecture, it feels that more than 75% of the content can be absorbed (Q7), and the teacher's lecture content is more in-depth than offline (Q8).

According to Tables 4 and 5, the reliability coefficient of 0.884 > 0.7 and the reliability criterion is high, indicating that the questionnaire meets the criteria. The questionnaire reliability deleted or corrected data are lower than the Alpha value of 0.884, which indicates that the design of the questionnaire meets the criteria.

Table 4: Reliability analysis of the platform teaching effect investigation

Cronbach's Alpha	Cronbach's Alpha based on standardized terms	Number of items
0.884	0.895	8

Table 5: Data of questionnaire reliability after deletion or correction

Project	The variance of the scale after deleting the item	Revised term and total correlation	Square multiple correlation	Cronbach's Alpha after deleting the item
Q1	22.635	0.695	0.541	0.854
Q2	23.528	0.648	0.467	0.862
Q3	22.476	0.762	0.614	0.848
Q4	25.132	0.483	0.295	0.875
Q5	24.184	0.645	0.452	0.864
Q6	22.325	0.562	0.358	0.873
Q7	23.617	0.673	0.501	0.857
Q8	23.406	0.724	0.546	0.854

(2) Validity analysis

The results of the validity measures of the platform teaching effectiveness survey are shown in Table 6. The results of the correlation matrix and significance of the platform teaching effectiveness are shown in Table 7.

According to the validity measure in Table 6 as well as Table 7, the KMO value is 0.904, which is significantly higher than 0.7, which is enough to show that this survey meets the standard. In the correlation matrix, the data are almost all in the range of 0.35-0.75, and the perspective of sample size, as well as combined with the analysis of significance, indicates a high degree of correlation between the data.

Table 6: Validity measurement of the platform teaching effect investigation

KMO sampling appropriateness measurement	0.904
Approximate chi-square	1402.182
Degree of freedom	26
Significance	0.000

Table 7: The correlation matrix and significance of the teaching effect of the platform

Project		Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Correlation matrix	Q1	1.00	0.63	0.69	0.37	0.53	0.48	0.54	0.61
	Q2	0.64	1.00	0.57	0.44	0.56	0.43	0.49	0.57
	Q3	0.71	0.59	1.00	0.38	0.49	0.65	0.64	0.64
	Q4	0.37	0.43	0.36	1.00	0.51	0.29	0.42	0.39
	Q5	0.52	0.54	0.53	0.52	1.00	0.42	0.46	0.57
	Q6	0.46	0.41	0.58	0.36	0.39	1.00	0.54	0.46
	Q7	0.55	0.45	0.64	0.42	0.45	0.55	1.00	0.61
	Q8	0.61	0.62	0.65	0.37	0.61	0.49	0.66	1.00
Significance	Q1	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Q2	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	Q3	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00
	Q4	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00
	Q5	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00
	Q6	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00
	Q7	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00
	Q8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

IV. C. 3) Survey and analysis of the effectiveness of the platform's classroom lectures

(1) Analysis of Students' Satisfaction with Teachers

There are 12 questions involved in this questionnaire survey, 8 of which are analyzed by Likert scale, and 345 samples are surveyed. The basic situation of the samples and the descriptive statistics of the effect of online classroom instruction are shown in Table 8 and Table 9 respectively. It can be seen that the distribution of students in the three grades is relatively even, and the proportion of males among male and female students is lower than that of females. For the results of the answers to the sample questions, after dividing the extreme difference by the variance, the scores are less than 5, and the absolute values of skewness and kurtosis are less than 1. The results of the questionnaire meet the standards.

Table 8: Basic information of the sample

	Gender		Grade			Educational background
Basic information of the sample	Male	Female	Freshman	Sophomore	Junior	Undergraduate (currently enrolled)
345	108	237	81	144	120	345
Percentage /%	31.30	68.70	23.48	41.74	34.78	100

Table 9: Descriptive statistics of the teaching effect of online classrooms

Project	N	Minimum value	Maximum value	Mean value	Standard deviation	Variance	Skewness	Kurtosis
Q1	345	1	5	3.5	0.974	0.961	-0.364	-0.23
Q2	345	1	5	3.64	0.932	0.893	-0.375	-0.424
Q3	345	1	5	3.61	0.938	0.905	-0.391	-0.406
Q4	345	1	5	3.95	0.915	0.844	-0.925	0.714
Q5	345	1	5	3.82	0.843	0.732	-0.581	0.716
Q6	345	1	5	3.47	1.126	1.517	-0.516	-0.853
Q7	345	1	5	3.53	0.875	0.796	-0.403	-0.041
Q8	345	1	5	3.39	0.865	0.782	-0.218	-0.249

Among the questions in the questionnaire, the scale questions, 8 items, mainly examined the effect of students' listening to the lectures delivered through the platform, and among the 8 items, 3 items mainly examined the teachers' lectures on the platform, which were Q2, Q5, and Q8.Now, the survey results of Q2, Q5, and Q8 were conducted. The results of the satisfaction survey on the interaction between teachers and students on the platform are shown in Table 10, and the results of the satisfaction survey on teachers' preparation and depth of lectures are shown in Table 11.

For teachers' attitude and seriousness of preparation and interaction in the classroom, the results show that in the students are satisfied and recognize the effectiveness of teachers' preparation, and there are more interactive sessions in online lectures than offline. According to Table 11, students in the top 20 of the class expressed the highest uncertainty about the depth of the teacher's lesson content, reflecting the fact that this group of students has a very high learning attitude as well as motivation. It is also suggested that teachers can dig deeper into the knowledge of the textbook and adjust the content of the lectures with appropriate difficulty matching.

Table 10: A survey on the satisfaction of interaction between teachers and students

Grade	Degree of satisfaction	Gender		Total	The proportion of the grade survey /%
		Male	Female		
Freshman	Not satisfied	3	6	9	11.11
	Uncertain	1	18	19	23.46
	Satisfied	11	28	39	48.15
	Very satisfied	7	7	14	17.28
	Total	22	59	81	100.00
Sophomore	Very dissatisfied	0	1	1	0.69
	Not satisfied	13	15	28	19.44
	Uncertain	12	24	36	25.00
	Satisfied	19	34	53	36.81
	Very satisfied	10	16	26	18.06
	Total	54	90	144	100.00
Junior	Very dissatisfied	1	0	1	0.84
	Not satisfied	3	6	9	7.50
	Uncertain	5	19	24	20.00
	Satisfied	25	45	70	58.33
	Very satisfied	8	8	16	13.33
	Total	42	78	120	100.00
Total	Very dissatisfied	1	1	2	0.58
	Not satisfied	19	27	46	13.33
	Uncertain	18	61	79	22.90
	Satisfied	55	107	162	46.96
	Very satisfied	25	31	56	16.23
	Total	118	227	345	100.00

Table 11: Satisfaction survey on the depth of teachers' lesson preparation and teaching

Survey Topic	Q5				
Degree of satisfaction	Class ranking 1-10	Class ranking 11-20	Class ranking 21-30	Class ranking ⩾31	Total
Very dissatisfied	3	2	1	0	6
Not satisfied	4	3	2	0	9
Uncertain	28	36	16	4	84
Satisfied	58	81	25	8	172
Very satisfied	20	30	16	8	74
Total	113	152	60	20	345
Survey Topic	Q8				
Very dissatisfied	3	2	0	0	5
Not satisfied	16	31	8	1	56
Uncertain	36	58	22	5	121
Satisfied	41	55	28	9	133
Very satisfied	7	15	7	1	30
Total	103	161	65	16	345

(2) Analysis of Students' Effectiveness in Classes

Among the 8 scale questions in this questionnaire, the survey on students' effectiveness in class involves the questions Q3, Q6 and Q7.The results of the survey on satisfaction with the learning efficiency of course content streamlining are shown in Table 12. The results of the satisfaction survey on note-taking in the course are shown in Table 13. The results of the satisfaction survey on absorption of lecture content are shown in Table 14.

Combined with the data analysis, it can be seen that the students of the three grades are more satisfied with the content of the teacher's lectures, accounting for 43.38%. However, uncertainty ranked second in the survey of the three grades, and in the teachers' future lectures, it is recommended that teachers clarify the content of the lectures' key points, prepare the lectures in a targeted way, and make the teaching design in advance. Meanwhile, 141 students were satisfied with the absorption rate of more than 75% after the online class. The highest percentage of satisfied students was 37 out of 81 students in the freshman year. And the highest proportion of 144 students in the sophomore year was uncertain. Therefore, teachers should be more flexible in teaching sophomores and focus more on guidance to cultivate students' pride in their major and increase their awareness of it.

Table 12: A survey on the satisfaction of learning efficiency with concise course content

Evaluation	Freshman	Sophomore	Junior	Total	Proportion /%
Very dissatisfied	0	2	5	7	2.03
Not satisfied	7	31	11	49	14.20
Uncertain	26	45	31	102	29.57
Satisfied	42	48	60	150	43.48
Very satisfied	6	18	13	37	10.72
Total	81	144	120	345	100.00

Table 13: Satisfaction survey on course note-taking

Degree of satisfaction	Class ranking 1-10	Class ranking 11-20	Class ranking 21-30	Class ranking ⩾31	Total
Very dissatisfied	14	15	2	0	31
Not satisfied	22	32	8	2	64
Uncertain	13	18	6	3	40
Satisfied	40	59	32	6	137
Very satisfied	23	28	14	8	73
Total	112	152	62	19	345

Table 14: Satisfaction survey on the Absorption of teaching content

Evaluation	Freshman	Sophomore	Junior	Total	Proportion /%
Very dissatisfied	0	4	4	8	2.32
Not satisfied	11	25	9	45	13.04
Uncertain	25	53	41	119	34.49
Satisfied	37	48	56	141	40.87
Very satisfied	8	14	10	32	9.28
Total	81	144	120	345	100.00

V. Conclusion

The interdisciplinary platform for rural revitalization talent cultivation in the context of digital economy constructed in this study has achieved remarkable results. Through the in-depth mining of data from five major recruitment platforms, three types of talent prototypes, namely, professional and technical, operation and management, and local returnee, are accurately identified, which provides a scientific basis for accurate cultivation. The developed interdisciplinary digital platform has perfect functions, integrating modules such as talent demand display, professional skills learning and data visualization. The empirical study shows that the teaching effect of the platform is remarkable: the Cronbach's alpha value of the questionnaire reaches 0.884, indicating the high reliability of the measurement tool, 162 students (46.96%) are satisfied with the classroom interaction of the platform, 150 students (43.48%) think that the course design is streamlined and efficient, 141 students (40.87%) say that the lecture content absorption rate exceeded 75%.

The study innovatively combines big data analysis with educational practice, providing a scalable solution for rural revitalization talent cultivation, which has important practical value for promoting agricultural and rural modernization.

In the future, the algorithm model can be further optimized to expand the application scope of the platform and enhance the precision of talent cultivation.

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