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Article

# Research and Application of Precision Talent Recruitment Driving Talent Selection Algorithms in Enterprises

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**Abstract:** When selecting talents, traditional enterprises set outdated as well as overly complex criteria, thus leading to the inability of enterprises to select suitable talents. For this reason, an enterprise talent selection algorithm based on FCM-PSO is proposed. Taking the preparation of enterprise talent selection as the starting point of this research, and setting enterprise talent selection indexes from three aspects: ability, attitude, and honor. Then use the network crawler technology to formulate the research data collection strategy, through the implementation of the strategy to obtain the research data, to provide data support for the subsequent development of the research work. Aiming at the FCM algorithm in the enterprise talent selection in the existence of local optimal situation, the PSO algorithm is used to optimize it, and finally complete the enterprise talent selection algorithm design work. Finally, the empirical analysis of enterprise talent selection algorithm is carried out from multi-dimension. Get 5 people only Q1 and Q4, to meet the requirements of enterprise talent selection, its algorithm output results for 1, 1, 1, not only verifies the algorithm in this paper in the enterprise talent selection in the practical application of the effect, but also for the enterprise precision talent recruitment to provide guidance.

**Keywords:** PSO algorithm; FCM algorithm; enterprise talent selection; web crawler

## 1. Introduction

In recent years, the human resource industry has undergone great changes, and accurate recruitment has become the main choice for enterprise recruitment [1-2]. In this competitive market, enterprises need to recruit talents more accurately to improve recruitment quality and efficiency [3-4]. However, traditional talent recruitment and selection methods often rely on manual empirical judgment and have many limitations, such as incomplete information, inefficiency, and subjectivity. With the continuous development and innovation of science and technology, artificial intelligence (AI) algorithms are more and more widely used in various fields [5-6]. Among them, AI algorithms are gradually introduced in the field of talent recruitment, which can improve the recruitment efficiency and select excellent talents [7].

The first step of talent recruitment is usually to screen a huge number of resumes, and AI algorithms can automatically parse, analyze and evaluate resumes through technologies such as natural language processing and machine learning [8-10]. It can recognize and extract key information in resumes, such as educational background, work experience, and professional skills, to quickly screen out candidates that meet the requirements [11-13]. Compared to manual screening, AI algorithms are able to process a large number of resumes in a short period of time, which greatly reduces the workload of HR departments [14-15]. Abhishek et al. [16] pointed out that manual screening of CVs in recruiting tasks faces challenges such as efficiency and the presence of bias, based on which the development of AI-driven CV analytics and recommendation tools effectively simplifies the CV screening process. Geetha and Bhanu [17] aimed to examine the impact of AI on recruitment strategies, emphasized the important role of AI in hiring decisions, and elaborated on the means employed by companies in using AI for recruitment. Barath et al [18] elaborated that the application of AI in the hiring process enhances the efficiency and effectiveness of the employment process, and proposed a data-based approach to improve resume



screening and the results showed that the approach effectively screened resumes. Pulavarthi et al [19] aimed to improve the speed and fairness of different resume screening systems with the help of Natural Language Processing and Machine Learning, which effectively addressed the key issues, i.e., dealing with informal data from resumes, dealing with algorithmic biases, and other criteria.

By analyzing job requirements and candidate resumes, AI algorithms can also intelligently match candidates based on job requirements and candidate skills to find the most suitable candidates, while further intelligent matching is performed by understanding candidates' interests, strengths, and personality traits [20-24]. This method of candidate matching not only improves recruitment efficiency, but also ensures that employers recruit people who are a high fit for the company's culture and values [25-26]. For example, Delecraz et al. [27] analyzed the issue of the proper use of AI in human resource management based on an algorithm development methodology for designing fairness, aiming to improve and automate recruitment efforts to find the best match with the position. Lee et al. [28] emphasized the importance of career matching for business development and examined several statistical analysis methods, proposing a method based on Artificial Intelligence and demonstrated that the method was able to improve job matching between university graduates and firms. Jirjees et al. [29] examined the BERT-based method which was able to provide more accurate candidate-job matching by utilizing deep contextual embedding to improve job seeker-job matching.

As for the interview assessment session, the traditional assessment method mainly relies on the subjective judgment of the interviewer, while the intelligent algorithm can provide objective assessment indicators and data support [30-31]. It can automatically assess the candidate's performance in the interview and provide relevant quantitative scores through technologies such as speech recognition and sentiment analysis [32-33]. This objective assessment approach reduces the personal bias and subjective judgment of supervisors and improves the fairness and accuracy of recruitment [34]. Son et al. [35] explored Artificial Intelligence Applied to Recruitment (AIR) and presented an inAIR for managing the recruitment process, emphasizing the value of the AIR in that it effectively broadens the communication channel between job seekers and HR managers. Aly et al. [36] discussed an AI-based recruitment system that securely manages candidate data, evaluates results that are highly compatible with human judgment, and provides a user-friendly experience. Uppalapati [37] examined the text generation AI model, GPT-3.5, to determine the applicability of a prompt-based text generation approach for generating responses for a specific student's scores, revealing that the model excelled in interview scoring by comparing model results with human values.

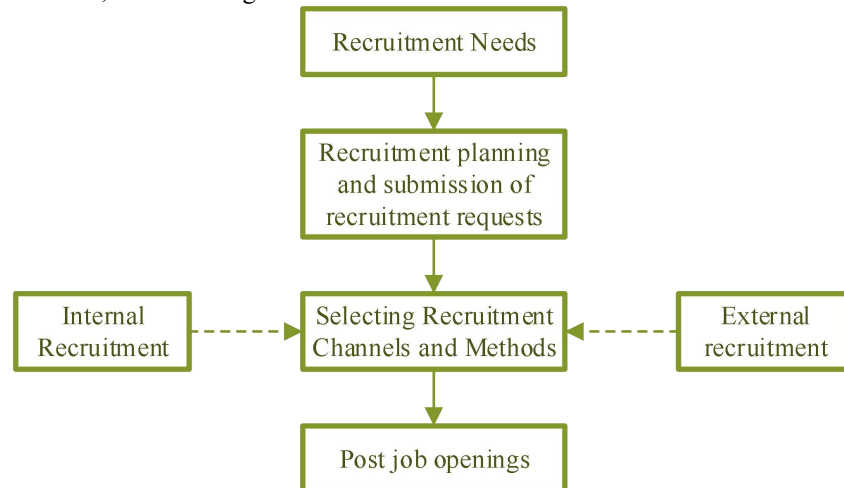
Although intelligent algorithms have been effective in improving the quality of recruitment in talent acquisition, the impact it brings is not perfect and even has risks, especially in terms of technological discrimination, ethics, etc. Chen [38] fills the research gap of algorithmic discrimination resulting from AI-driven recruitment, and based on the literature review shows that algorithmic bias may result in discriminatory hiring based on gender, ethnicity, and personality trait. Abdelhay et al. [39] pointed out that the application of AI in the recruitment industry not only reduces costs but also improves efficiency, and examined the challenges posed by AI based on semi-structured interviews. Ore and Sposato [40] discussed the risks of applying AI in talent selection, and based on in-depth interviews with multinational corporations showed that there are a number of risks associated with AI in talent selection. There are many risks, which trigger distrust among recruiters. Bhargava and Assadi [41] point out the non-instrumental values that are easily overlooked by the application of intelligent algorithms in interviewing, based on which human interviewing should not be replaced by algorithms. Haque [42] emphasizes the fact that AI has reshaped the hiring process and improved the objectivity of talent selection, but still faces a series of ethical and governance challenges, including the potential to exacerbate historical bias, increase workplace surveillance, and others.

This paper constructs a resume screening enterprise index system based on the content of the preparatory work before enterprise talent screening, from the three aspects of ability, attitude and honor. With reference to the current mainstream data acquisition methods, the final use of network crawler technology to collect the data for this research, which facilitates the following research work. Combined with the principle of FCM algorithm, the enterprise talent selection algorithm is designed, and it is found that there is a local optimal problem, which is optimized with the help of PSO algorithm, so as to realize accurate enterprise talent recruitment. Finally, the algorithm of this paper is empirically analyzed, aiming at verifying the practical application value of this paper's algorithm, and providing reference for enterprise talent assessment and screening work.

## 2. Research on enterprise talent selection under precise talent recruitment

### 2.1. Preparation before talent screening in enterprises

For enterprises, talent recruitment, resume screening is ultimately a problem for the classification of groups of people, which is more troubling for managers of start-up enterprises. Talent recruitment is a systematic project, which needs to be planned and implemented in stages according to scientific procedures, so as to improve the recruitment efficiency and recruit the talents needed by the organization. Figure 1 shows a schematic diagram of the recruitment planning work tasks, which can be divided into four stages, namely, determining recruitment needs, formulating recruitment planning, selecting recruitment channels, and releasing recruitment information.



**Figure 1.** Schematic diagram of the recruitment plan's work tasks.

### 2.2. Talent indicator setting for CV screening

Based on the positioning of the position of the enterprise is a technical engineer, after joining the company needs to be able to complete the task delivered through their professional skills, so the weight of the professional ability accounted for more, set at 50%, attitude accounted for 25%, honor accounted for 25%. The company released each position in the resume talent matching, the first need to meet the basic conditions set by the post: years of experience, work location, salary requirements, if there is a problem with one of these three items of information, it is not in line with the basic requirements of the company, either not in line with the candidate's requirements, and then subsequently to carry out the ability to match the attitude, honor and other information is meaningless. This can speed up the efficiency of resume matching retrieval, the first to carry out the satisfaction of the match, and then the indicator class match.

#### 2.2.1. Competence

Ability is the core concern of talent recruitment index point, can be supported by some objective data, and quality, morality, and professionalism aspects are required to reflect the process of long-term work, so the core competence of the recruiter is a more critical point of investigation [43]. And the ability contains many aspects, from the point of view of the personnel ability requirements of enterprise technology research and development engineers. Contains four secondary ability observation points, respectively, professional ability, management ability, communication and collaboration ability, learning ability.

#### 2.2.2. Attitudinal aspects

Attitude is the embodiment of a person's professionalism, sometimes the ability to be strong, in the attitude of the above problems, on the contrary, for the company is a greater tumor, affecting the whole team office environment. Attitude based on the current resume content screening summary, contains four observations, respectively, work intensity support, job adaptability, job-hopping cycle, work attitude.

#### 2.2.3. Honors

For the identity of the candidate is a freshman or a veteran of the workplace or not, there is no honor

of course does not affect the job search, there is a third-party assessment of the honor at least to apply for additional points. For example, for their own professional / skills to obtain a number of certificates: English four or six certificates, computer grade certificates, project manager certificates, database management engineers certificates, system architects, etc.; in the work of the honor of the excellent staff, excellent new employees, progress awards and so on. These honors can at least prove that their work results have been recognized by a third party.

### 2.3. Data acquisition

#### 2.3.1. Developing a Resume Collection Strategy

This paper combines the current popular web crawler technology + Baidu PaddleNLP (based on deep learning Chinese NLP open-source toolset) to help companies in the acquisition of resume data, extraction of keyword information in the resume to improve the efficiency of information acquisition. The data acquisition process is as follows:

##### (1) Add web crawler target

According to the current talent recruitment information released on the Internet platform, select the URL address of the Internet platform to add crawling, and at the same time pass the parameters of the two parameters (platform enterprise login account and password), use automatic scripting technology to complete the verification of the platform account to enter the enterprise side of the resume information list page.

##### (2) Setting the crawling area

Because the layout and layout of each page is different, we need to analyze and disassemble the page to be crawled before crawling the data. We believe that the two most valuable data areas of the page are: conditional screening, job announcement list. Then you need to locate the HTML code of the web page to set the region to get.

##### (3) Set the search strategy

###### (a) Indexing, categorization rules references

Crawler as a search engine, the core of the realization of a way to crawl the relevant data based on keywords to search for data in the region, to find the page data has a corresponding sub-word set the content.

###### (b) Search task mode

Crawler running in a variety of ways, for the characteristics of the data source in this scenario, should do a timed task mechanism to ensure that the dynamics of data acquisition, without the need for each time the human to trigger the acquisition of data, for example: we can set the Wednesday morning at 6:00 a.m. for the collection of data, of course, this time can be set flexibly, but also a certain time on Wednesday, or a certain month, and other time requirements, and secondly, we also need to set up the data CV crawling The periodicity of the data can be full or incremental data crawling.

##### (4) Return to match based on the split word disassembly

Based on the previous step of crawling to match, to find the resume data for the list, the list here is still the basic thesaurus search to crawl to the data, rather than crawling for the resume data itself for machine learning algorithms to calculate the degree of match of the resume.

##### (5) Output data

Output the entire list of crawled for the next stage of machine learning-based enterprise talent selection algorithm to provide data support.

#### 2.3.2. Curriculum Vitae Collection Strategy Implementation

This subsection will explain in detail how the current Internet platform for the automatic screening of resume collection work, in order to follow up based on the collection of screened resumes to analyze the results of matching. In this paper, in the above data collection methods, introduced to the use of web crawler technology + Baidu PaddleNLP (based on deep learning Chinese NLP open-source toolset), enterprise data R & D team in accordance with this paper to develop a resume collection and screening strategy plan, the use of spare time to build the ResumeRobot program project, running on the Ali cloud.

### 2.4. Machine Learning Based Algorithm for Enterprise Talent Selection

#### 2.4.1. Principles of the FCM algorithm

Clustering is the process of partitioning a dataset into classes or clusters according to a specific criterion, so that the similarity of data objects within the same cluster is as large as possible, and the

difference of data objects not within the same cluster is as large as possible [44]. Algorithms of the FCM type were first derived from the optimization of the objective function of a “hard” clustering, which extends the hard clustering algorithm to the fuzzy case. Hard clustering algorithms are generalized to the fuzzy case by not forcing the objects on the boundaries of several classes to be completely assigned to one of them. Instead, they are assigned affiliations of size between 0 and 1 to indicate their partial affiliation. Compared with K-means it has some flexibility and is more suitable for talent selection problems. The objective function  $J$  and constraints are as follows:

$$J = \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m \|x_j - c_i\|^2 \quad (1)$$

$$\begin{cases} \sum_{i=1}^c u_{ij} = 1 \\ u_{ij} \in [0, 1] \end{cases}, (i = 1, 2, \dots, c; j = 1, 2, \dots, n) \quad (2)$$

Where  $J$  consists of the distance from the sample to the clustering center multiplied by the affiliation degree of that sample;  $c$  is the number of clusters;  $n$  is the number of samples;  $m$  is the fuzzy weighted index;  $u_{ij}$  is the affiliation degree;  $x_j$  is the sample point; and  $c_i$  is the clustering center.

The affiliation degree and clustering center are updated as follows:

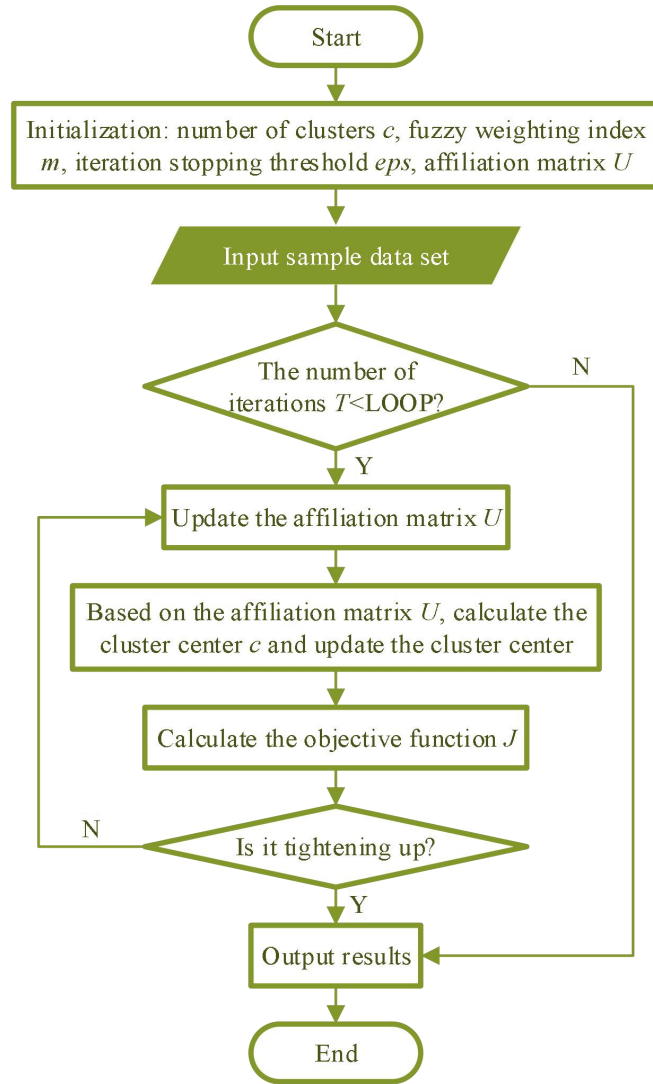
$$u_{ij} = 1 / \sum_{k=1}^c \left( \|x_j - c_i\| / \|x_j - c_k\| \right)^{(2/m-1)} \quad (3)$$

$$c_i = \sum_{j=1}^n u_{ij}^m x_j / \sum_{j=1}^n u_{ij}^m \quad (4)$$

The affiliation matrix  $U$  is:

$$U = (u_{ij})_{c \times n} = \begin{bmatrix} u_{11} & \cdots & u_{1n} \\ \vdots & \ddots & \vdots \\ u_{c1} & \cdots & u_{cn} \end{bmatrix} \quad (5)$$

When the FCM algorithm runs, it needs to establish the fuzzy similarity matrix, also called calibration. In this paper, the FCM algorithm uses the Euclidean distance to establish the fuzzy similarity matrix, and the specific flow of the FCM algorithm implementation is shown in Figure 2.



**Figure 2.** Flowchart of FCM algorithm

#### 2.4.2. Determining the optimal number of clusters for clustering

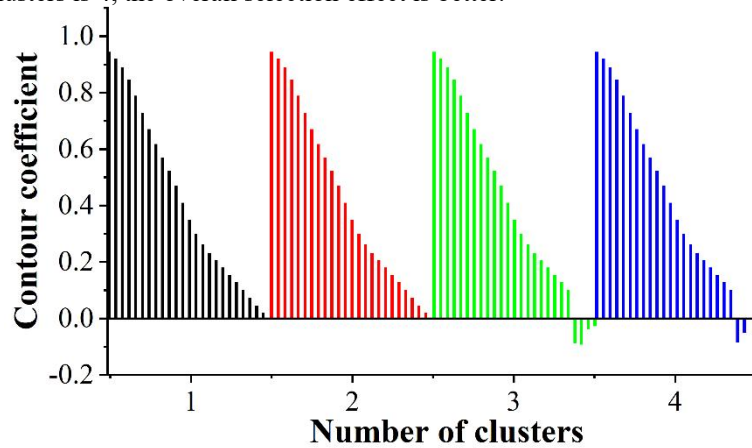
The contour coefficient combines cohesion and separation and is used to evaluate the effectiveness of clustering as a means of determining the optimal number of clusters. The contour coefficient value for each sample point in the cluster is calculated as follows:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (6)$$

where  $a(i)$  is the average distance from sample  $i$  to all other points in the cluster it belongs to, reflecting intra-cluster cohesion, and  $b(i)$  is the average distance from sample  $i$  to all points in the cluster closest to it, reflecting inter-cluster separation.

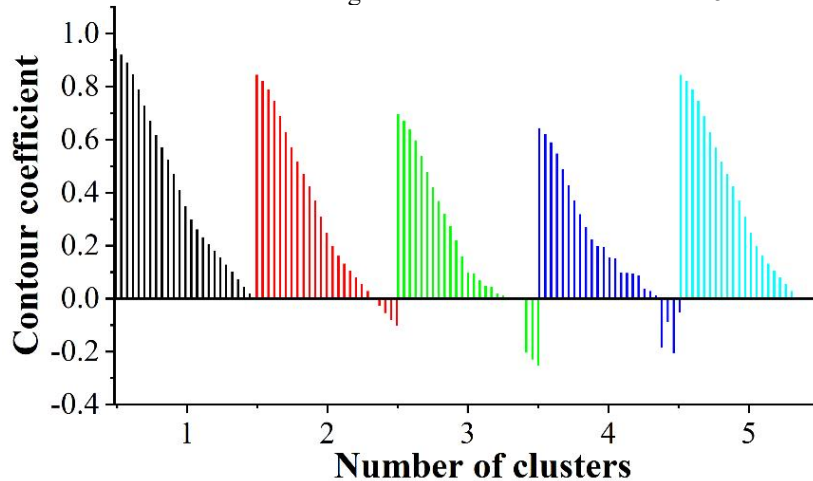
The contour coefficient  $S(i) \in [-1, 1]$ , whose value is closer to 1, indicates that the sample  $i$  is more suitable for the class, and vice versa, the closer it is to -1, indicates that the sample  $i$  is less suitable for the class, and it should be more appropriately assigned to other clusters. In this paper, the number of clustering clusters  $C$  is set to 4, 5 and 6 for the test, which results in the contour coefficients as shown in Fig. 3, Fig. 4 and Fig. 5 below, with the horizontal coordinate as the contour coefficients and the vertical coordinate as the number of clusters. Figure 3 shows the distribution of contour coefficient value when the number of clusters is 4, each rectangle in the figure represents the contour coefficient value of a sample. 125 groups of sample data are divided into four categories under the FCM algorithm, the contour coefficient value is greater than 0, there are 100 groups of samples and most of them have a value greater

than 0.3, which indicates that the effectiveness of the talent selection results is high. There are 5 groups of samples smaller than 0, and a few samples have values close to 0, indicating that the error is small. When the number of clusters is 4, the overall selection effect is better.



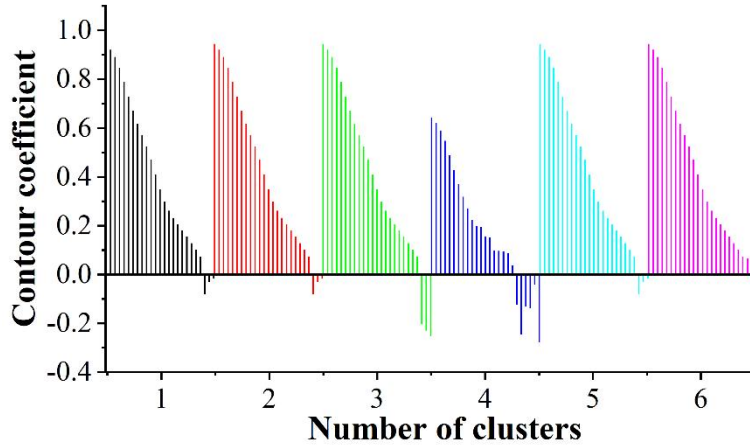
**Figure 3.** Contour coefficient graph when the number of clusters is 4

Figure 4 represents the distribution of contour coefficient values when the number of clusters is 5. Category 1 and category 5 have better results, category 2, category 3 and category 4 have individual samples with contour coefficient values less than 0, and there are allocation errors. Category 3 has a total of 25 groups of samples, 4 groups of samples are assigned with errors, and the selection effect is poor. Therefore, the overall selection effect is average when the number of clusters is 5.



**Figure 4.** Contour coefficient graph when the number of clusters is 5

Figure 5 represents the distribution of contour coefficient values when the number of clusters is 6. From the figure, it can be observed that sample assignment errors occur in all clusters. Among them, there are 25 sets of samples in the clusters of category 4, and there are 7 sets of samples with error, which is the largest error, and the overall selection effect is poor. By analyzing the profile coefficient diagrams from Figure 3 to Figure 5 above, it is determined that the optimal number of clusters is 4, with fewer errors, which can well meet the talent selection needs of enterprises.



**Figure 5.** Contour coefficient graph when the number of clusters is 6

### 2.4.3. Particle Swarm Algorithm Optimization

In order to get the optimal initial clustering center and clustering results, combined with the advantages of simple operation and fast convergence of particle swarm (PSO) algorithm, we introduce the particle swarm optimization algorithm to optimize the initial randomly generated initial affiliation matrix, and then get the optimal initial clustering center and clustering results after the computation, so as to make the algorithm achieve a better classification effect. The basic idea of the PSO algorithm is to regard each value in the randomly generated affiliation matrix as a searching individual in the N-dimensional search space, and regard its current region as a candidate solution to be obtained. The basic idea of the PSO algorithm is to regard each value randomly generated in the affiliation matrix as a searching individual in the N-dimensional search space, regard the region where it is currently located as a candidate solution of the optimal affiliation matrix to be obtained, and determine the optimal individual extremum by adjusting the speed and position of each value in the matrix, so as to obtain the optimal solution of the affiliation matrix for the population [45]. Repeatedly loop to update the velocity and position of the affiliation matrix particles to obtain the optimal solution that satisfies the final end condition. The steps to optimize the initialized affiliation matrix in conjunction with the PSO algorithm are:

- (1) Generate the initial affiliation matrix randomly.
- (2) Evaluate the fitness value of each affiliation in the matrix.
- (3) If the current of the affiliation is greater than the historical optimal value, update the historical optimal position.
- (4) If the historical optimum of the particle is better than the global optimum, update the affiliation matrix population optimal solution.
- (5) Stop when the maximum number of iterations is reached or a set threshold is reached, otherwise jump to step (3).

## 3. Empirical Analysis

### 3.1. Algorithm Validation Analysis

#### 3.1.1. Experimental program

The source of experimental data is the web crawler described above, including data information on ability, attitude, honor, etc. The FCM-PSO algorithm model designed in this paper is used to cluster and analyze the data of corporate talent resumes. The model parameters are set as follows:

- (1) The population size is 50.
- (2) The maximum number of iterations is 200.
- (3) The termination iteration error of the objective function is 1~7.
- (4) The weighting parameter is 4.0.
- (5) The clustering center is 4 (given above and not repeated here).

In order to evaluate the effect of each clustering, this paper utilizes the tightness to evaluate the accuracy of the FCM-PSO algorithm. Its calculation formula is:

$$\overline{CP}_i = \frac{1}{|\Omega_i|} \sum_{x_i \in \Omega_i} \|x_i - w_i\| \quad (7)$$

$$\overline{CP} = \frac{1}{K} \sum_{K=1}^K \overline{CP}_K \quad (8)$$

Where: CP is the average distance from each point of each class to the clustering center is calculated. The smaller CP is, the closer the clustering distance is within the class.

### 3.1.2. Experimental results and analysis

The CP values of the labels are obtained through 30 experiments, and the results are shown in Table 1. From the experimental results, it can be seen that the CP value of the clustering results fluctuates less, is very stable, and does not easily fall into the local optimal solution, thus verifying the accuracy of the model.

**Table 1.** The CP value of the PSO-FCM experimental results.

Number of Experiments	CP value		
	Ability	Attitude	Honor
1	3.0950	3.0667	3.0186
2	3.0784	2.9072	3.0936
3	2.9451	2.9120	3.0606
4	3.0465	3.0962	2.9945
5	2.9932	2.9248	3.0865
6	3.0632	2.9545	3.0360
7	2.9461	3.0380	3.0619
8	3.0481	3.0122	2.9671
9	3.0937	2.9118	2.9603
10	2.9040	2.9583	2.9669
11	2.9341	3.0160	3.0474
12	2.9664	3.0305	3.0371
13	2.9547	2.9598	2.9391
14	3.0725	2.9493	3.0728
15	2.9750	2.9645	2.9677
16	3.0901	3.0429	3.0693
17	2.9437	3.0532	3.0609
18	2.9524	2.9914	2.9939
19	3.0613	3.0175	3.0105
20	3.0574	3.0796	3.0983
21	3.0168	2.9985	3.0231
22	2.9128	3.0847	2.9162
23	2.9900	2.9185	2.9920
24	3.0528	2.9178	2.9418
25	2.9978	2.9299	2.9478
26	2.9663	2.9212	2.9266
27	3.0609	3.0310	2.9302
28	3.0792	3.0933	3.0464
29	2.9139	3.0598	2.9959
30	3.0241	3.0038	3.0345
Average	3.0079	2.9948	3.0099

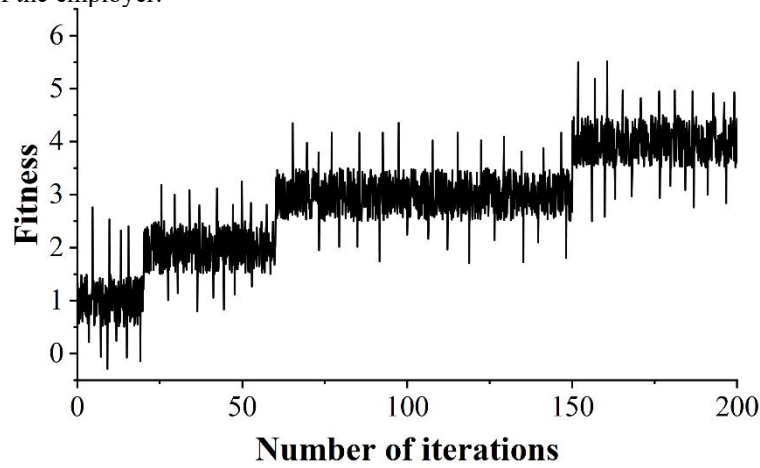
From the above, when the clustering center  $c=4$ , its clustering effect is significant. Therefore, the number of clustering centers set in the experiment should be 4. In order to be able to explicitly rate the subjective labels of the talent resume data, the researcher applies the actual situation in the recruitment, and the categories after clustering of each subjective label are used as excellent, good, fair, and poor, respectively. Next, the clustering result samples obtained by FCM-PSO are utilized for training, so as to predict the new sample data. The researcher divided the experimental data into training set and validation set according to the ratio of 4:1. Take capacity as an example for analysis. Set the population size  $Size=50$  and the maximum number of evolutionary generations is 200. The adaptation function is chosen

as Eq. (9):

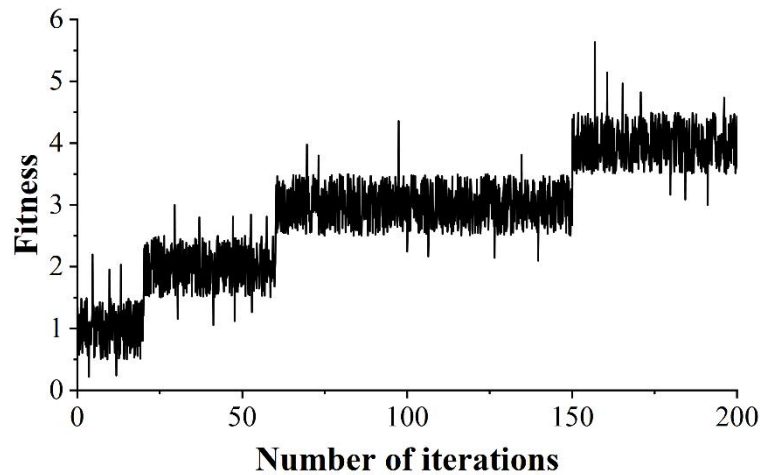
$$f = \frac{1}{\sqrt{\sum (y_i - \hat{y}_i)^2}} \quad (9)$$

Where:  $y_i$  is the confirmation category of the sample and  $\hat{y}_i$  is the observed value. The larger the error, the smaller the function value and the smaller the fitness value.

The performance of FCM algorithm is shown in Fig. 6 and the performance of FCM-PSO algorithm is shown in Fig. 7. The traditional FCM adaptation value of 1.09 and the FCM-PSO adaptation value of 1.44 are obtained through experiments. It can be seen that the FCM-PSO algorithm has a lower error rate and a higher adaptation value than the traditional FCM, which not only has a better overall performance effect, but also greatly reduces the training cost, which confirms the validity and feasibility of the enterprise talent selection algorithm based on FCM-PSO. Due to the short communication time between the employer and the candidate, it is difficult for the employer to accurately assess the comprehensive quality of the candidate, which results in problems such as low success rate of signing or unreasonable arrangement of positions after successful signing. In view of this phenomenon, employers in the recruitment process can use the algorithm in this paper to understand the comprehensive ability of the students, the recruiter can be very intuitive and fast to complete a comprehensive understanding of the applicants, preliminary screening of unqualified candidates, and initially determine the applicants to adapt to the position, reducing the consumption of material resources and manpower, and saving the cost of recruitment of the employer.



**Figure 6.** Performance of the FCM algorithm.



**Figure 7.** Performance of the FCM-PSO algorithm.

### 3.2. Algorithm Application and Example Analysis

### 3.2.1. Algorithm application analysis

When collecting data in real life, it is often necessary to obtain as many features of the data as possible, resulting in a large number of features that are less relevant to the actual problem are also mixed in. There are many features in the HR database of an enterprise, including the basic information of the employees, such as name, gender, ethnicity, date of birth, place of origin, job status, publication status, marital status, etc., but there are a lot of features that are irrelevant to the task of interest, i.e. redundant features. If these features are not removed in advance, it will be difficult to obtain effective clustering results. The data used in the experiment comes from an enterprise's human resource database, which records the personal situation, academic degree, professional and technical position, work experience and other information of 2000 employees. According to the comprehensive suggestions of many experts, representative features are selected, including: department, ethnicity, gender, age, length of service, education (degree), graduation time, graduation institution, specialty, current job position, nature of work, title level, time of obtaining title, time of hiring, party affiliation and so on. The main body of this paper's research is the job applicant, so 1,000 records of the applicant are screened from the database. The experiments were conducted by trying  $k=4$  and  $k=5$  respectively, and the work ability was quantified into four grades of I, II, III and IV from high to low.

The clustering results at  $k=4$  are shown in Table 2. The number (percentage) of people in categories I through IV were 337 (33.7%), 253 (25.3%), 184 (18.4%), and 226 (22.6%), respectively. The first category consisted mainly of young male candidates with a doctoral degree, who had just joined the company recently and had already been recognized as a senior title with a strong working ability. The second category is mostly middle-aged female candidates, with rich working experience, long graduation time, slow updating of knowledge, title level still stuck at intermediate, and relatively weak working ability. The third category is mostly middle-aged male candidates, graduated in a long time, the working age are longer, the title level is mostly intermediate, the relative scientific research ability is not strong. The fourth category is mostly middle-aged and elderly male candidates, with longer years of service, doctoral degrees, title level of senior, and strong working ability.

**Table 2.** The clustering result of  $k=4$ .

Classification	Gender	Age	Length of service	Graduate School	Degree	Professional title	Ability	N
1	Male	25~30	0~5	A	Doctor	Advanced	II	337
2	Female	31~35	5~10	B	Master's degree	Intermediate level	III	253
3	Male	35~40	10~15	C	Bachelor's Degree	Intermediate level	III	184
4	Male	40~45	15~18	D	Doctor	Advanced	I	226

The clustering results for  $k=5$  are shown in Table 3, where the number (percentage) of people in the first through fifth categories are 168 (16.8%), 157 (15.7%), 191 (19.1%), 139 (13.9%), and 345 (34.5%), respectively. This clustering result is based on  $k=4$ , retaining the first and fourth of the four categories, while reclassifying the second and third categories into a new three categories, characterized as follows: the second category is mostly young female candidates, with short school years, some of which have long working years, and the other has short working years, and they have not graduated for a long time, even though they have a doctoral degree, with a title level of intermediate, and they do not have a lot of work achievements. The third category is mostly middle-aged and old-aged male applicants, with longer working years, early graduation from the University, low academic level, although rated as senior title, but due to their age, their knowledge system is more outdated, and their working ability is weaker. The fourth category is mostly middle-aged female candidates, all with longer working age, with intermediate title level and weaker research ability. In summary, it shows the application effect of the algorithm of this paper in the process of enterprise talent selection, and provides guidance for enterprise talent recruitment.

**Table 3.** The clustering result when  $k=5$ .

Classification	Gender	Age	Length of service	Graduate School	Degree	Professional title	Ability	N
1	Male	25~30	0~5	A	Doctor	Advanced	II	168
2	Female	31~35	5~10	B	Master's degree	Intermediate level	III	127
3	Male	35~40	10~15	C	Bachelor's Degree	Intermediate level	III	191
4	Female	35~40	10~15	E	Master's degree	Intermediate	IV	139

						level		
5	Male	40~45	15~18	D	Doctor	Advanced	I	345

### 3.2.2. Algorithm Example Analysis

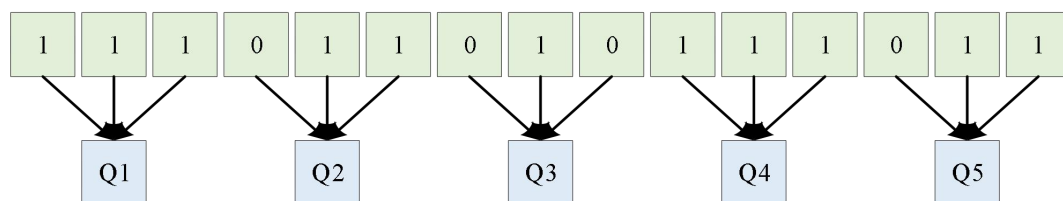
Research a limited company to get the basic data, and data preprocessing, the number of participants in the selection of 5, then the number of particle clusters is 20, the size of the group is 200, randomly generate the initial number of groups is 20. The values of each initial index of the five individuals participating in the selection process are shown in Table 4. The algorithm is programmed using Turbo C, and the results of the operation obtained are shown in Table 5. As can be seen in Table 5, when the number of iterations is 160 and 200, the change in the value of the degree of fitness is 0.008 and 0.003 (much less than 0.01), respectively, and therefore the operation is stopped. At this time, the output optimal combination is shown in Figure 8. Figure 8 shows that the decision maker should choose the individuals numbered Q1 and Q4 to participate in the selection because only Q1 and Q4 are all 1. It indicates that the honor of the two individuals numbered Q1 and Q4 is optimal, and the enterprise should include these two individuals in the assessment when selecting talents. The other individual particles in some positions for 0, because these individuals of a certain indicator below a certain threshold. For example, the number Q2 and Q5 are not enough to work, and the individual numbered Q3 is not outstanding in ability and honor performance. Through the analysis of this example, it fully proves the value of this paper's algorithm in enterprise talent selection, and provides technical support for enterprise accurate talent recruitment.

**Table 4.** The processed data of each indicator value.

The number of the talent participating in the selection	Ability	Attitude	Honor
Q1	85	91	88
Q2	71	89	84
Q3	72	86	71
Q4	84	89	88
Q5	70	82	84

**Table 5.** The results of different algebraic operations.

Please pass the algebra (h)	Fitness value (f)
40	0.747
80	0.818
120	0.916
160	0.924
200	0.927



**Figure 8.** Output result.

## 4. Conclusion

Aiming at the current problem of accurate talent recruitment and selection in enterprises, this paper designs an enterprise talent selection algorithm based on FCM-PSO on the theoretical basis of machine learning algorithms, and empirically analyzes the application value of the algorithm. The research results of this paper are as follows:

(1) Compared with the traditional FCM algorithm, the FCM-PSO algorithm has a lower error rate and a higher adaptation value, which not only verifies the optimization effect of particle swarm algorithm (PSO) on fuzzy clustering algorithms, but also demonstrates the practical application effect of the FCM-PSO algorithm in the enterprise talent selection work.

(2) Using this paper's algorithm to analyze the five enterprise applicants from Q1 to Q5, it is found that only Q1 and Q4 meet the requirements of enterprise talent selection, and their outputs are all 1, which highlights the effect of this paper's algorithm in the application of the work of enterprise talent selection, and provides guiding theoretical value for the enterprise's precise talent recruitment and

selection.

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