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*Research Article*

# Research on an Artificial Intelligence-Based Professional Ability Evaluation System from the Perspective of Industry-Education Integration

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The rapid development of artificial intelligence technology demands higher requirements for employment and talent training. The integration of industry and education is an important way to solve the mismatch between industrial demand and talent supply. Therefore, this study starts from the perspective of the integration of industry and education. We collect recruitment texts from the perspective of "industry" and mine the specific requirements of the artificial intelligence post system through the LDA topic model and the combination of Word2Vec and *K*-means. We then conduct expert consultations and adjust the selected indicators from the perspective of "education." Finally, we construct a four-dimensional vocational ability grade evaluation index system, including basic vocational skills of artificial intelligence, database, network skills, algorithm and design skills, and research and practice skills. The intuitionistic fuzzy analytic hierarchy process, which can eliminate the subjective uncertainty of experts in the scoring process, is applied to calculate the index weights. We find that the weight of algorithm and design skill is the highest, which is an important criterion for artificial intelligence professional ability evaluation. Among the second-level indicators, practical indicators such as team spirit, innovation ability, and communication ability are the focus of investigation from the perspective of industry, while in education, the cultivation of knowledge and skills such as programming ability, applied mathematics ability, data structures, and algorithms are more important.

## 1. Introduction

In the 21st century, based on the advent of the Internet [1–3], the Internet of Things [4–6], big data [7], cloud computing [8, 9], and other technologies, machine learning and in-depth learning have gradually matured [10, 11]. Massive datasets have gradually taken shape and accelerated the integration of artificial intelligence and clouds [12]. At the same time, the requirements of real-time businesses have forced the artificial intelligence computing ability to continuously penetrate to the edge [13, 14] and end [15]. A new wave of artificial intelligence is rising all over the world, giving birth to a number of disruptive technologies, accelerating the cultivation of new drivers of economic development, shaping emerging industrial systems, and leading a new round of scientific and technological revolution and industrial change. The developmental trends of artificial intelligence in recent years are reflected not only in the iterative innovation of technology but also in the expansion of application fields. For example, these trends are evident in the intelligent analysis of education evaluation in the education industry [16], intelligent risk monitoring and investment prediction in the financial industry [17, 18], intelligent monitoring and control of UAVs and vehicles [19, 20], the efficient scheduling and management of dynamic resources [21–24], and other fields closely related to the economy and people's livelihood, such as intelligent cities [25, 26], intelligent medical treatment [27, 28], intelligent communication [29], and intelligent infrastructure [30, 31]. All these trends reflect the intelligent upgrading of traditional industries. According to the Artificial Intelligence and Life in 2030 Report of the 2015 Study Panel of Stanford University, artificial intelligence has been rapidly developed and highly applied in many fields, including transportation, family services, health care, education, public safety, work, and employment.

The rapid development of artificial intelligence technology and applications has had a great impact on employment and talent training. On the one hand, because technological progress improves productivity increases, some labor can be directly replaced by machines, and employment discrimination is becoming increasingly serious [32]. On the other hand, artificial intelligence promotes the expansion of the industrial scale and the upgrading of structure, thus creating new jobs and new employment opportunities and improving work quality [33]. Gartner, a consulting firm, predicts that from 2020, the number of jobs created by artificial intelligence will exceed the amount of unemployment caused by it. In particular, it will create 2.3 million new jobs while "eliminating" 1.8 million jobs. The development of artificial intelligence puts forward new requirements for the talent market. These new requirements also transfer the power of change to the talent training of colleges and universities.

The development of artificial intelligence benefits from the requirements of economic development for new technology, while the demand for emerging talent brought by technological development deepens the integration of industrial and educational reforms in talent training. The integration of industry and education helps to complement the long-standing shortcomings of talent training at all levels and provides strong talent support for economic transformation and upgrading and technological iteration. It will also help to meet the actual requirements of those to be employed to master the skills required in the industry. Therefore, this paper evaluates the professional ability of AI practitioners from the perspective of the integration of industry and education and constructs an AI professional ability evaluation index system. Our specific research route is as follows:

(i) First, strong information support is obtained through literature research and text mining. The late Dirichlet allocation (LDA) topic model is used to divide different types of artificial intelligence posts. The combination of Word2Vec and K-means can extract the career needs of different posts. Based on this, the index factors of the evaluation system are preliminarily conceived and designed.

(ii) Second, the index is pruned or modified in combination with expert consultations. Furthermore, the reliability and validity of the questionnaire are tested through a large sample.

(iii) Then, the weights of each level and each index of the index system are calculated by the fuzzy analytic hierarchy process method.

(iv) Finally, combined with the research results, this paper analyses the emphasis on different indicators in the process of artificial intelligence professional ability evaluation and puts forward corresponding suggestions for artificial intelligence industry enterprises and talent training institutions.

The research framework is shown in Figure 1.

This paper evaluates the professional ability of artificial intelligence from the new perspective of the integration of industry and education, creatively takes the text mining results as one of the bases for the selection of evaluation indicators, and makes the following main contributions:

(i) The constructed artificial intelligence professional ability evaluation index system provides a reference for the artificial intelligence industry to evaluate the professional ability of relevant talent. It also provides guidance and a basis for human resource management and recruitment for artificial intelligence enterprises.

(ii) The constructed index system defines the future learning and development directions for the employees in the artificial intelligence industry. They can use the evaluation index system to self-evaluate and choose the appropriate fields to deepen their learning and thereby improve their overall quality and skill levels.

(iii) In the process of constructing the index system, different categories of posts in the artificial intelligence industry have been identified. The skill needs of various dimensions of the artificial intelligence industry have also been clarified. As a result, various talent training institutions can formulate artificial intelligence talent training programs according to their basic education facilities, scientific research education levels, and education development orientations. By improving students' skill levels, their employment rate will also improve.

The rest of this paper is organized as follows: Section 2 summarizes the relevant research. The characteristics of artificial intelligence vocational ability evaluation from the perspective of industry-education integration are described in Section 3. Section 4 presents the main research methods used in this study. Section 5 is the most important part of the article. In this section, the preliminary selection of indicators is completed based on the text mining results, and the final indicator system is determined through the Delphi method and a questionnaire survey. Then, the index weights of the constructed system are calculated in Section 6. Finally, in Section 7, we analyze and summarize the research results and put forward some suggestions regarding the reform of talent training.

## 2. Related Work

*2.1. The Demand for Talent Training in Artificial Intelligence.* Professional ability evaluation is a worldwide issue that plays an important role in students' employment and further education, enterprise recruitment, and the development of the educational ability of colleges and universities. A large amount of research has been conducted on the talent demand for artificial intelligence and the evaluation and reform of talent training from the perspective of industry-education integration. Wang and Ren [34] divided the types of artificial intelligence posts into three levels: the basic level, technical level, and application level. Li and Chen [35]

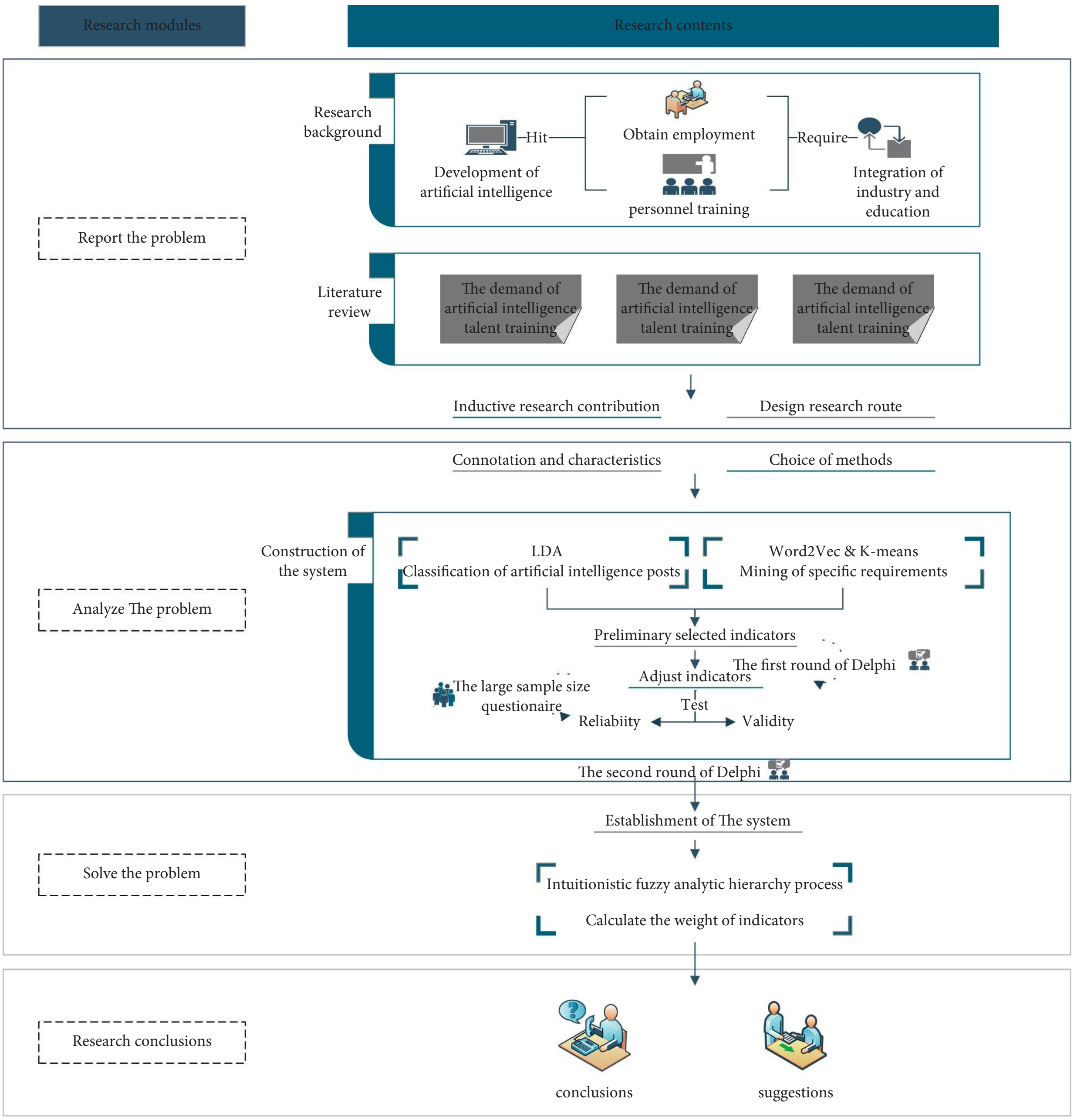


Figure 1: The research process framework diagram.

divided the types of artificial intelligence talent into three types: the basic research type, application practice type, and technology R&D type, with different emphases on the needed abilities. Huang [36] stated that based on the development orientation and professional characteristics of the artificial intelligence specialty, its professional knowledge structure should be considered at five levels: the infrastructure layer, core technology layer, supporting technology layer, system platform layer, and application layer.

*2.2. Mismatch between Education and the Labor Market.* Existing studies also pay attention to the inherent mismatch between education and the labor market. The reasons for this mismatch and the resulting waste of human resources, including "overeducation" and "insufficient education," have been studied in [37]. This mismatch has a negative impact on the wage levels of employees and the national macroeconomy [38]. In the era of artificial intelligence, the mismatch between people and positions has not been solved, but it has become more serious. According to the European Centre for the Development of Vocational Training (CEDEFOP), by 2025, approximately 48% of jobs in Europe will only be for employees with higher education qualifications, and 85% of European jobs will require at least one basic digital skill. In the period of rapid technological change, to fill the skill gap and help individuals maintain their employment success rate and continuous progress, individuals need to receive lifelong vocational education. In addition, the intelligent reform of talent training strategies in educational institutions is necessary to solve problems such as weak discipline, specialty construction, and the insufficient innovation of talent training modes [39]. Thus, the integration of industry and education is a good direction for talent training reform.

*2.3. Reform Based on the Integration of Industry and Education.* In December 2017, the general office of the State Council issued "Several Opinions on Deepening the Integration of Industry and Education." It started with the construction of an overall integrated development pattern of education and industry that will promote the reform of talent training for the integration of industry and education and the two-way connection between the supply and demand of industry and education. This is intended to promote the organic connections between the education chain, talent chain, industrial chain, and innovation chain. The aim is to realize the sharing of resources and information between schools and enterprises and realize "win-win" outcomes for school education, enterprises, and students. Subsequently, Dong and Huang [40] proposed that vocational education in the era of artificial intelligence should develop intelligently on the basis of the existing cooperation mode, group mode, industry-education integration mode, and other collaborative development. Hu [41] pointed out that the essence of industry-education integration is to create connections between school education and social needs through complementary advantages and resource sharing between enterprises and universities. Through innovative organizational forms and production management modes, one must realize new technology development, achievement transformation, and collaborative education. Ren and Liu [42] proposed that to build a talent training platform integrating industry and education, colleges and universities should actively establish contacts with enterprises, apply theoretical research results to the research and development of artificial intelligence products, and adopt the "system of bilateral contractual employment" to appoint teachers in the field of artificial intelligence.

*2.4. Research Review.* Looking at the existing related studies, it is found that traditional and emerging vocational ability evaluation index systems have similarities but are also different in their dimensions and methods. It is also clear that there is no clear view on the professional ability evaluation of talent in the artificial intelligence industry to solve the long-term mismatch between education and the labor market. The integration of industry and education is an effective angle to solve the severe mismatch between talent training and demand, and it has become an active new direction of higher education reform research. The promotion of related policies has formulated the "$1+X$" technical talent training standard and framework for a new wave of higher vocational education research. However, it has not been applied to the research of artificial intelligence talent training reform and talent professional ability evaluation. Therefore, this paper constructs a talent professional ability evaluation index system, which provides a reference for developing artificial intelligence talent in colleges and universities and the employment criteria of enterprises.

## 3. Connotation and Characteristics

*3.1. Artificial Intelligence Professional Ability Evaluation.* Professional ability is a collection of various skills that should be possessed in a certain occupation. It is not only the ability of people to comprehensively use knowledge, experience, and skills to complete professional tasks but also the basic requirement of competence for a job. Professional ability evaluation needs to measure and evaluate specific groups according to the ability needs of professional talent and the corresponding evaluation system. In the same industry, due to different job functions, their professional ability requirements can be different. Talent in the field of artificial intelligence not only must possess general basic abilities but also must master the professional knowledge of artificial intelligence and hone professional skills according to the individuals' own professional plans. Other requirements are R&D ability, the ability for continuous learning, and the ability to integrate all aspects of experience and resources in innovation. The integration of industry and education occurs due to the in-depth cooperation carried out by colleges and universities to improve the quality of talent training and to meet the talent needs of enterprises. The two sides complement each other to realize the organic connection between the college education chain, talent chain, enterprise industry chain, and innovation chain. The existing research on professional ability evaluation for an industry often takes the enterprise as the perspective and the professional skill level as the focus to build the index system, while college education often takes academic achievements as important standards for talent training evaluations. Therefore, the evaluation of artificial intelligence professional ability should separate professional ability from the needs of college training and the artificial intelligence industry, set ability standards, and build professional ability evaluation standards in line with the needs of industrial development.

*3.2. Purpose and Characteristics of Artificial Intelligence Professional Ability Evaluation.* The purpose of artificial intelligence professional ability evaluation is to provide a basis for human resource management and the talent recruitment of artificial intelligence enterprises. Second, it must help practitioners conduct self-assessment, help choose areas for deeper learning, and provide a reference framework for self-development. Third, it should provide a reference basis for the cultivation of artificial intelligence talent in colleges and universities, help optimize the artificial intelligence curriculum, and cultivate "artificial intelligence +" talent in various industries. To ensure that the evaluation results of AI professional ability from the perspective of industry-education integration are meaningful, we must be aware of the characteristics of the evaluation process.

(1) Diversity of evaluation indicators:

According to the theory of multiple intelligences, the ways of human thinking and understanding are diverse, and the ability to solve a problem or create a product is also diverse. Therefore, there should also be diversity in the evaluation of talent functions. The professional ability of artificial intelligence talent often carries out a comprehensive and diversified evaluation from the aspects of basic quality, professional skills, research practice, and so on. Accordingly, scientific and diverse methods, such as self-evaluation, evaluation by others, quantitative indexes, and fuzzy evaluation should also be used in the evaluation process to ensure the accuracy of evaluation and the effectiveness of results.

(2) Hierarchy of evaluation systems:

Industry practitioners have different work fields and are required to perform different tasks. Different posts often imply certain differences in competency levels. The required vocational skills are different and have different hierarchical standards. Therefore, the artificial intelligence vocational ability evaluation system should also be hierarchical to meet the needs of artificial intelligence posts at different levels.

(3) Comprehensive evaluation of experts:

From the perspective of the integration of industry and education, the construction of the evaluation system and the selection of evaluation experts should be comprehensive. The professional ability of talent should be evaluated from the perspective of education and employment. One must comprehensively evaluate the professional ability of the evaluated object, make the ability level of employees clear, clarify the ability gap and deepen the learning direction.

## 4. Methods

*4.1. Text Mining.* The era of big data has driven an increase in electronic text information, which contains a large amount of valuable intelligence. Text mining refers to the process of applying technologies and algorithms to extract potential and valuable knowledge from a large number of unstructured or semistructured text sets. The emergence and development of its key technologies are based on massive text information. In addition, in the existing research on vocational ability evaluation, the selection of indicators often relies on literature research, summarizes the commonly used indicators in previous research, or adds interviews and consultations with experts in the field. Taking the mining results of enterprise recruitment texts as the basis for the selection of indicators from the perspective of "industry" is more practical and persuasive than making decisions through literature research or expert consultation.

The data volume of enterprise recruitment text is large, but it has a relatively clear text structure. The LDA topic model in the text mining method can project high-dimensional sample data into the optimal classification vector space. The extracted topic subspace has a larger distance between different categories and a smaller distance within the same category to complete the classification of different artificial intelligence positions. The enterprise recruitment text also has a short length and the text has a strong semantic relevance. The Word2Vec word vector model can convert natural language symbols that cannot be directly understood by computers into specific vectors that can be recognized by computers and take into account the semantic links between words. The $K$-means clustering algorithm has higher efficiency and accuracy in processing short texts. Therefore, this study combines Word2Vec with $K$-means, which can effectively solve the problem of clustering the information on professional ability needs in the short text of enterprise recruitment represented by the vocabulary.

(1) Latent Dirichlet Allocation (LDA):

The latent Dirichlet allocation (LDA) topic model is a three-layer Bayesian topic model with a "text-topi-words" structure [43]. The bag-of-words method is used to convert the text into word frequency vectors. Assuming that several topics form a document according to a certain probability and several words determine the topic according to a certain probability, document to topic and topic to vocabulary obey a polynomial distribution. The mathematical description of the model is as follows:

Step 1: For each document $d \in D$, the document length is $N$, and the subject probability distribution of the sampled generated document $d$ is $\theta_d \sim \text{Dirichlet}(\alpha)$.
Step 2: Subject $Z_{d,i}\,(i \in \{1,2,3\ldots N_d\})$ can be obtained according to multinomial distribution $Z_{d,i} \sim \text{Multinomid}(\theta_d)$.
Step 3: For each topic $z \in K$, the lexical probability distribution of the sampled topic $z$ is $\phi Z_{d,i} \sim \text{Dirichlet}(\beta)$.
Step 4: According to the multinomial distribution $W_{d,i} \sim \text{Multinomid}(\phi Z_{d,i})$, the word $W_{d,i}\,(i \in \{1,2,3\ldots N_d\})$ can be obtained.

The joint distribution formula of the whole model is expressed as formula (1):

$$p(w, z, \theta_d, \phi_k | \alpha, \beta) = \prod_{i=1}^{N} p(\theta_d|\alpha) p\left(Z_{d,i}|\theta_d\right) p(\phi_k|\beta) \cdot p\left(W_{d,i}|\phi Z_{d,i}\right). \quad (1)$$

In this formula, $\alpha$, $\beta$ and $k$ are preset hyperparameters; normally, $\alpha$ and $\beta$ are default values, and $k$ is the most appropriate number of topics. $\theta$, $\varphi$ and $z$ are the latent parameters to be inferred and calculated and $w$ is the observation parameter.

The graphic representation of LDA is shown in Figure 2.

The word segmentation results are converted into structured data, and this is taken as the object to

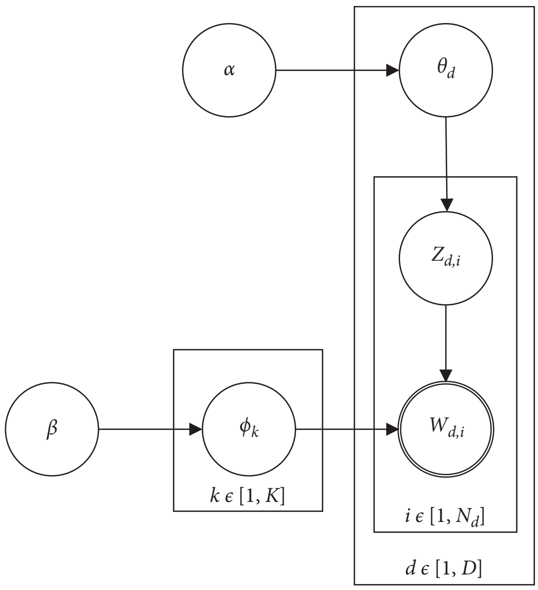


Figure 2: Graphic representation of LDA topic model.

build the LDA topic model. Then, the method of calculating perplexity is used to assist in determining the optimal topic number $k$ of the four types of text. The calculation formula of perplexity is shown in:

$$\text{Perplexity}(D) = \exp\left\{-\frac{\sum_{d=1}^{M} \log P(W_d)}{\sum_{d=1}^{M} N_d}\right\}, \quad (2)$$

where $D$ is the test document set, $W_d$ is the vocabulary sequence of document $d$, $P$ $(W_d)$ is the probability of $W_d$ in document $d$, and $N_d$ is the vocabulary number of document $d$.

(2) Combination of Word2Vec and $K$-means:

Word2Vec is an open-source computing tool based on the idea of deep learning and has a three-layer neural network language model structure of "input layer-hidden layer-output layer." It can convert vocabulary into a high-dimensional vector through the training of a text dataset to realize the feature quantization of vocabulary text [44]. Word2Vec fully considers the relationship between words and context and includes two common models: the CBOW model and the skip-gram model. The CBOW model takes the long following words of the target vocabulary as the input to predict the target vocabulary probability, while the Skip-Gram model takes the target vocabulary as the input to predict the context vocabulary probability. The selected text dataset is the recruitment demand text in the field of artificial intelligence. The semantic tendency of the dataset is relatively concentrated, and the vocabulary frequency of ability demand is high and has a strong connection with the context. Therefore, this study selects the CBOW model to embed high-frequency keywords with a frequency of more than 300. The structure of the CBOW training model is shown in Figure 3, where $\omega$ represents the word in the text.

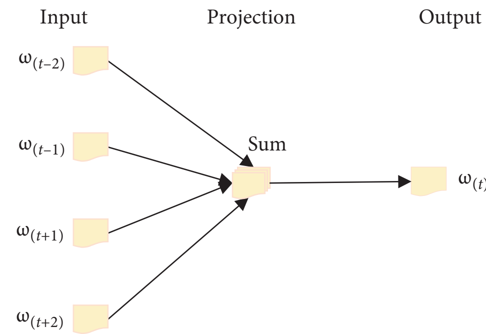


Figure 3: The structure of the CBOW training model.

The $K$-means algorithm is a dynamic clustering algorithm based on sample distance. It reduces the similarity between clusters through iterative optimization of unsupervised learning of clustering rules. Compared with other clustering algorithms, the $K$-means algorithm is simpler and more effective, with low computational time complexity and strong stability when processing high-dimensional data [45]. In this study, the silhouette coefficient is used as the judgment basis for the selection of the $k$ value of clustering. The calculation formula of the individual silhouette coefficient is shown in:

$$S_i = \frac{b_i - a_i}{\max(a_i, b_i)}, \quad (3)$$

where $a_i$ is the average distance between sample $i$ and other samples in the same category, and $b_i$ is the average distance between sample $i$ and its nearest internal samples in other categories. The average value of the individual silhouette coefficient of all samples is the global silhouette coefficient, and the calculation formula is as follows:

$$S_k = \frac{1}{n}\sum_{i=1}^{n} S_i. \quad (4)$$

The character $n$ represents the number of samples, and $k$ represents the number of clusters. The higher the $S_k$ value is, the more reasonable the sample clustering result.

Word2Vec is combined with $K$-means to complete the text mining task from vectorization to final clustering to obtain different categories of all words in the text.

*4.2. Intuitionistic Fuzzy Analytic Hierarchy Process.* The traditional analytic hierarchy process has both significant advantages and disadvantages. While the evaluation process is intuitive and concise, it depends too much on the subjective experience of experts. Based on this, Van Laarhoven and Pedrycz [46] fuzzified the analytic hierarchy process, and Buckley [47] formally proposed the fuzzy analytic hierarchy process on this basis. The fuzzy analytic hierarchy process combines the inclusiveness of the fuzzy set and the

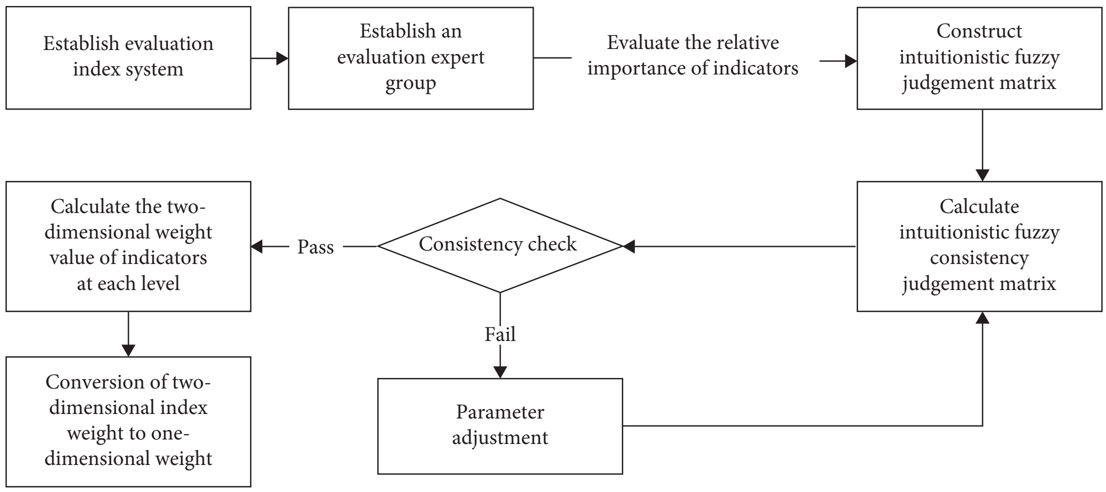


Figure 4: Flow chart of the intuitionistic fuzzy analytic hierarchy process.

quantification of the analytic hierarchy process. This reduces the influence of experts' subjective factors, but its judgment matrix has difficulty achieving the expected results in the consistency test and has limitations on the expression of experts' hesitation in the process of judgment. Atanassov [48] extended the intuitionistic fuzzy set theory to the three states of "subordinate," "nonsubordinate," and "hesitation" in the intuitionistic fuzzy set. This allows the expert evaluation to have the three attitudes of support, opposition, and neutrality. It is integrated into the analytic hierarchy process to form the intuitionistic fuzzy analytic hierarchy process to make up for the shortcomings of the past methods. In this paper, the intuitionistic fuzzy analytic hierarchy process is used to calculate the weight, and the specific process is shown in Figure 4.

## 5. Construction of the Index System

Based on the characteristics of artificial intelligence professional ability evaluation and following the principles of scientific, comprehensive, feasible, qualitative, and quantitative combination, this paper collects and analyses enterprise recruitment texts, integrates and divides the types of artificial intelligence posts, interprets the professional needs of different posts, analyses the common indicators of professional ability evaluation in combination with expert consultation and literature research, and comprehensively constructs a hierarchical index system of professional ability evaluation of artificial intelligence talent.

*5.1. Artificial Intelligence Post Type Extraction Based on LDA.* This paper uses a program compiled by Python to obtain 12531 enterprise recruitment texts retrieved with "artificial intelligence" as the keyword from a recruitment website. The program deletes duplicate records, records of posts in the non-artificial intelligence industry, and records with incomplete text content and finally retain 10,138 recruitment texts. In the text preprocessing stage, the keywords "job requirements," "application requirements," "qualification," "position request," "hire requirements," and other keywords are replaced by "position requirements." The program is used to divide the post tasks and post requirements within the boundary of "position requirements." We manually handle text records that do not meet this format as exceptions and find and delete irrelevant information such as workplace, welfare benefits, and company profile through regular expression.

Different AI posts have their own preferences for the educational level of talent. Matching the processed recruitment text with the minimum educational requirements of the post through keywords helps to extract different AI posts from a large number of recruitment texts. After matching, 598 text records indicated positions requiring an associate degree or above, 4,752 records requiring a bachelor's degree or above, 3,217 records requiring a master's degree or above, 202 records requiring a doctoral degree, and 1,369 records not indicating academic requirements are obtained. We then randomly select 500 recruitment information as the dataset, carefully read and built the dictionary of common terms in the recruitment text, enrich the stop word list, segmented the four types of text, and remove the stop words in the word segmentation results.

The value of perplexity generally decreases gradually with the increase in $k$, the number of potential topics. A lower degree of confusion represents a higher model generation ability. Therefore, the $k$ value of the lower point or inflection point of the curve describing perplexity is selected to substitute into the LDA training model to judge the text topic classification results. The results show that the optimal number of topics for texts with a minimum requirement of an associate degree is 3, the optimal number of topics for texts with a minimum requirement of a bachelor's degree is 5, and the optimal number of topics for texts with a minimum requirement of a master's degree is 5, and the optimal number of topics for texts with a minimum requirement of a doctoral degree is 2. Because different enterprises have different educational requirements for the same post, the text classification

Table 1: Artificial intelligence post topics extracted by LDA topic model.

| Order number | Educational requirements | Subject words | Subject | Positions included |
|---|---|---|---|---|
| A1 | Associate degree or above | 0.012 * automation + 0.010 * communication + 0.009 * debugging + 0.008 * responsibility + 0.008 * computer + 0.007 * team spirit + 0.007 * project + 0.007 * responsible + 0.006 * relevant + 0.006 * electronic + 0.006 * office + 0.005 * maintenance | Basic application post | Product sales<br>Account manager<br>R & D assistant |
| A2 | | 0.025 * automation + 0.016 * development + 0.014 * robot + 0.013 * C# + 0.013 * correlation + 0.012 * computer + 0.011 * debugging + 0.011 * algorithm + 0.011 * C++ + 0.010 * programming + 0.009 * business trip + 0.009 * image processing | Technical support post | Test engineer |
| A3 | | 0.013 * computer + 0.010 * system + 0.009 * technology + 0.009 * related + 0.008 * development + 0.007 * automation + 0.007 * responsibility + 0.006 * algorithm + 0.006 * learning + 0.005 * communication + 0.005 * electronics + 0.005 * attitude | Application development post | Search engine engineer<br>NLP engineer |
| B1 | Bachelor's degree or above | 0.026 * ability + 0.018 * experience + 0.015 * technology + 0.012 * communication + 0.011 * computer + 0.011 * software + 0.011 * development + 0.009 * design + 0.009 * product + 0.009 * responsibility + 0.008 * project + 0.007 * work experience | Technical support post | Technical support engineer<br>Product manager |
| B2 | | 0.024 * algorithm + 0.024 * control + 0.022 * robot + 0.018 * development experience + 0.017 * C++ + 0.015 * ROS + 0.013 * experience + 0.013 * development + 0.012 * computer + 0.011 * mathematics + 0.011 * system + 0.010 * C | Application development post | Search engine engineer<br>NLP engineer<br>Speech recognition engineer |
| B3 | | 0.031 * development + 0.019 * programming + 0.016 * development experience + 0.015 * Linux + 0.014 * experience + 0.014 * embedded + 0.014 * C++ + 0.013 * C + 0.011 * system + 0.011 * platform + 0.009 * electronics + 0.009 * framework | Application development post | Embedded engineer |
| B4 | | 0.027 * algorithm + 0.025 * image processing + 0.021 * machine vision + 0.021 * experience + 0.019 * vision + 0.018 * C++ + 0.017 * automation + 0.014 * computer + 0.011 * image + 0.011 * development + 0.010 * capability + 0.010 * C | Application development post | Computer vision engineer |
| B5 | | 0.031 * algorithm + 0.019 * ability + 0.018 * mathematics + 0.018 * deep learning + 0.017 * machine learning + 0.016 * computer + 0.015 * experience + 0.015 * python + 0.012 * C++ + 0.010 * domain + 0.009 * technology + 0.009 * language | Algorithm research post | Machine learning direction<br>Data mining direction |

Table 1: Continued.

| Order number | Educational requirements | Subject words | Subject | Positions included |
|---|---|---|---|---|
| C1 | Master's degree or above | 0.028 * algorithm + 0.020 * robot + 0.019 * control + 0.015 * C + + + 0.012 * experience + 0.012 * C + 0.012 * automation + 0.011 * planning + 0.011 * capability + 0.010 * development experience + 0.010 * computer + 0.009 * ROS | Application development post | Search engine engineer<br>NLP engineer<br>Speech recognition engineer |
| C2 | | 0.031 * algorithm + 0.023 * signal processing + 0.017 * experience + 0.013 * C + + + 0.012 * communication + 0.012 * C + 0.012 * electronics + 0.012 * capability + 0.011 * mathematics + 0.010 * simulation + 0.010 * computer + 0.010 * MATLAB | Application development post | Embedded engineer |
| C3 | | 0.044 * image processing + 0.032 * algorithm + 0.025 * image + 0.023 * C + + + 0.018 * pattern recognition + 0.016 * C + 0.016 * computer + 0.015 * math + 0.015 * vision + 0.014 * detection + 0.014 * OpenCV + 0.014 * programming | Application development post | Computer vision engineer |
| C4 | | 0.028 * algorithm + 0.020 * machine learning + 0.020 * ability + 0.019 * deep learning + 0.017 * experience + 0.015 * domain + 0.014 * computer + 0.014 * mathematics + 0.013 * Python + 0.011 * technology + 0.009 * model + 0.009 * C++ | Algorithm research post | Machine learning direction<br>Data mining direction |
| C5 | | 0.013 * ability + 0.012 * deep learning + 0.012 * C++ + 0.011 * domain + 0.011 * computer + 0.011 * algorithm + 0.010 * C + 0.010 * python + 0.010 * experience + 0.009 * computer vision + 0.009 * publication + 0.009 * conference | Senior R & D post | Team leader |
| D1 | Doctoral degree | 0.029 * algorithm + 0.015 * experience + 0.015 * deep learning + 0.014 * mathematics + 0.012 * calculation + 0.011 * C++ + 0.010 * artificial intelligence + 0.010 * C + 0.009 * computer + 0.009 * machine learning + 0.008 * ability + 0.008 * python | Senior R & D post | Senior algorithm researcher |
| D2 | | 0.019 * ability + 0.013 * experience + 0.012 * algorithm + 0.011 * field + 0.011 * technology + 0.010 * machine learning + 0.009 * deep learning + 0.008 * computer + 0.008 * project + 0.008 * publication + 0.008 * paper + 0.007 * artificial intelligence | Senior R & D post | Artificial intelligence expert |

results of different educational requirements overlap. The combined AI post topics are shown in Table 1.

We carefully read the original text corpus used to refine the topics of different AI posts and integrate five main types of AI posts by analyzing their post name, job description, educational requirements, and ability requirements, including basic application posts, technical support posts, application development posts, algorithm research posts, and senior R&D posts. Among the extracted topics, $A1$ covers most of the basic application posts, including product sales, account managers, and R&D assistants. The topics of $A2$ and $B1$ are technical support posts, of which $A2$ mainly includes test engineers, and $B1$ mainly includes technical support engineers and product managers. The $A3$, $B2$, $B3$, $B4$, $C1$, $C2$, and $C3$ topics are application development posts. Topic $B3$ and $C2$ identify embedded development posts responsible for underlying development and software embedding. Machine vision development direction post requirements are reflected in topics $B4$ and $C3$. Search engine development, natural language processing, speech recognition, and other application development posts are mainly concentrated in the $A3$, $B2$, and $C1$ topics. The algorithm research post is concentrated under the $B5$ and $C4$ topics, mainly in two directions: machine learning and data mining. $C5$, $D1$, and $D2$ topics are classified as senior R&D posts, including the team leader, who leads the enterprise AI team; the senior algorithm researcher responsible for the efficient optimization of existing algorithms and the research and development of core intelligent algorithms and cooperating with the engineering team to realize the engineering implementation of algorithms; and artificial intelligence experts who overcome the technical difficulties in the research and development of core algorithms to maintain the leading position of algorithms and are responsible for the precipitation of scientific research achievements and product transformation. The artificial intelligence posts corresponding to the extracted topics are sorted, and the results are shown in Figure 5.

Among the five types of artificial intelligence posts, the basic application posts in the artificial intelligence industry are mainly responsible for the sales promotion of artificial intelligence products, customer relationship maintenance, and other auxiliary work. Talent is required to have the general basic skills and qualities necessary for all industries. Those in technical support posts need to master customer needs and project progress, complete project installation, commissioning, and training, identify problems in artificial intelligence projects and products and provide solutions, provide professional support for the industry, and have professional knowledge and technology such as data processing and network programming. Artificial intelligence application development posts require skills in search engines, natural language processing [49], speech recognition, embedded development, and computer vision [50]. Accordingly, talent is required to have deep knowledge in one or several directions. The algorithm research posts include two major directions: machine learning or deep learning and data mining. It is required for talent in these posts to master common algorithms and frameworks and to be able to form opinions on the R&D and design of algorithms. The advanced research and development positions of artificial intelligence require the team to carry out project development in the enterprise, plan the development of the AI team, protect the advanced nature of the algorithm, and at the same time be responsible for the enterprise's patent deployment and research output. The demand for talent is the lowest but these posts require the talent to have a deeper development experience and R&D capability.

*5.2. Extraction of the Professional Ability Requirements of Artificial Intelligence Posts Combined with Word2Vec and k-Means.* We accumulate the four types of text word segmentation results into a complete recruitment demand text dataset, set the "min_count" parameter of Word2Vec to 300, that is, vectorize the words after word segmentation with a frequency greater than 300, and finally, $K$-means cluster the vectorized dataset. The global silhouette coefficient is iteratively calculated as $k$ takes different values, and a broken line diagram is drawn, as shown in Figure 6.

After the $k$ value reaches 15, the results of word vectorization clustering combined with Word2Vec and $K$-means, merging synonyms and eliminating irrelevant words, are shown in Table 2.

The clustering results of vocabulary show that most AI enterprises require talent to have a certain computer level, have the ability to quickly read materials in English, communicate well, actively cooperate, and constantly learn and innovate, while bearing the pressure of work. There is also a relatively concentrated professional demand for talent. The posts correspond to different educational levels. At a deeper level, talent is required to have a certain number of years of work experience and project development experience and to produce high-quality academic achievements. On the premise of mastering the basic knowledge of algorithms, theory, and data processing, it is also necessary to flexibly use common programming languages such as C++, C, Python, and Java to be familiar with different operating system development environments. Enterprises also require talent to have skills in product design, software, and hardware testing. Data mining and analysis, common algorithms, and deep learning frameworks are also high-demand professional skills and knowledge. Computer vision and image processing are currently the hot directions for development posts. In addition, there are increasing requirements for digital signal processing and simulation, industrial robot technology, etc.

*5.3. Selection of Indicators.* To objectively evaluate the professional ability of artificial intelligence talent, we must select the professional ability evaluation indices from many directions and angles and establish the hierarchical structure of multi-index evaluation. There is a certain mismatch between the demand for artificial intelligence talent in enterprises and artificial intelligence teaching in colleges and universities. More precisely, enterprises prefer professional

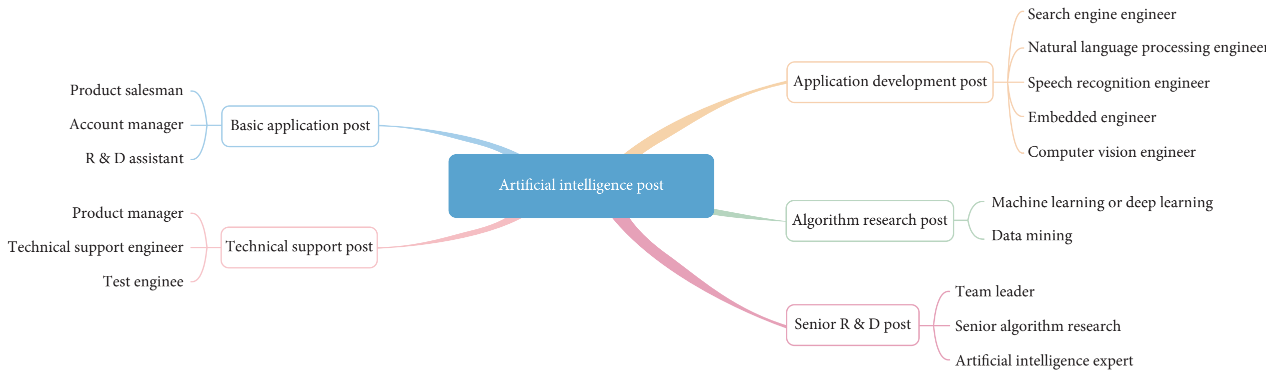


Figure 5: Artificial intelligence job classifications.

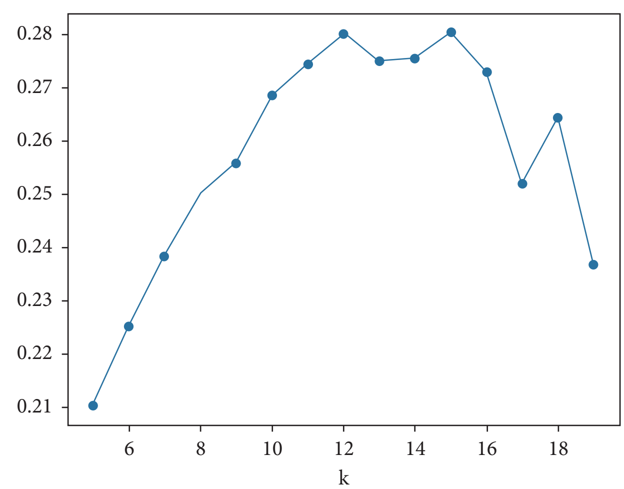


Figure 6: Variation trend of global silhouette coefficient.

skills and experience, while colleges and universities prefer knowledge and quality training. Enterprise recruitment text analysis summarizes the ability needs from the perspective of "industry." Therefore, this paper integrates the perspective of "education" through expert consultations, combined with literature research on talent training in colleges and universities. After this, we finally build an index system along four dimensions: basic quality, data processing, network programming skills, algorithm and design skills, and research and practice skills. Based on expert opinions, the selected indicators are added, deleted, and adjusted, and 32 second-level indicators, as shown in Figure 7, are preliminarily selected.

The Delphi method is then used to determine the final evaluation index system. Twenty-six experts from artificial intelligence enterprise technology R&D personnel, management personnel, and college artificial intelligence teachers were invited as team members, and an expert correspondence questionnaire was designed. The questionnaire included the experts' basic information, the experts' familiarity with the indicators, the Likert scale with the increasing importance of each indicator from 1 to 5 points, and the basis for judging the importance. The experts' familiarity with each index and the judgment basis of expert importance in the questionnaire are quantified to form the expert authority. The calculation formula of authority $C_r$ is

$$C_r = \frac{C_a + C_s}{2}, \tag{5}$$

where $C_a$ represents the basis for expert importance judgment, and the assignment from high to low is practical experience, relevant research, theoretical analysis, and intuitive judgment. $C_s$ represents the arithmetic mean of the value of experts' familiarity with each index. The average authority $C_r$ of the expert object in the first round of correspondence was 3.46, indicating that the selected experts are authoritative. The critical value method was adopted for the screening of indicators, and the indicators with an arithmetic average value of importance lower than 3.8, a full score ratio lower than 55%, and a coefficient of variation higher than 0.3 in the results of the first round of correspondence were deleted. To ensure preciseness, a large sample size questionnaire survey was conducted on the remaining indicators before the second round of Delphi. Taking the managers and technical R&D personnel of enterprises whose business scope involves artificial intelligence as well as the teachers and students of artificial intelligence-related majors in colleges and universities as the objects, 160 questionnaires

Table 2: Demand topics extracted by vocabulary vectorization clustering.

| Category | Vocabulary | Refined demand |
|---|---|---|
| N1 | Computer<br>Automation<br>Electronic engineering<br>Math<br>Software engineering<br>Signal communication<br>Applied mathematics | Professional background |
| | Undergraduate<br>Master<br>Doctor | Educational level |
| | More than 1 year<br>More than 2 years<br>More than 3 years<br>More than 5 years<br>Work experience<br>Relevant working experience | Work experience |
| N2 | Algorithm principle<br>Theoretical basis<br>Basic skills<br>Modelling<br>Algorithm development<br>MATLAB<br>Data processing | Professional basic knowledge |
| N3 | Teamwork spirit<br>Teamwork ability<br>Steadfast<br>Responsibility<br>Communication skills<br>Learning ability<br>Innovative consciousness<br>Compressive capacity<br>Problem-solving ability<br>Logical thinking ability<br>Expressive ability | Basic quality |
| N4 | SLAM<br>Robot<br>Motion<br>Control<br>Sensor<br>ROS<br>Plan<br>Navigation | Industrial robot technology |
| N5 | Open-source framework<br>TensorFlow<br>PyTorch<br>Deep learning framework<br>Caffe | Common open-source frameworks |
| N6 | Statistics<br>Data<br>Big data<br>Data mining<br>Data analysis | Data mining and data analysis |

Table 2: Continued.

| Category | Vocabulary | Refined demand |
|---|---|---|
| N7 | Debugging<br>Software development<br>Test<br>Hardware equipment | Software testing and hardware debugging |
| | Design<br>Technological process<br>Product | Product design |
| N8 | Code<br>Network<br>Database<br>Development experience<br>Embedded<br>Development | Development experience |
| | Operating system<br>Linux<br>Environment | Mainstream operating system development environment |
| N9 | C<br>C++<br>Python<br>Java<br>Programming language<br>Data structure<br>Programming ability | Programing language |
| N10 | Image processing<br>3D<br>OpenCV<br>Halcon<br>Machine vision | Computer vision development software and technology |
| N11 | Technology<br>Research and development<br>Artificial intelligence<br>Field<br>Project experience | Research and project experience in the field |
| N12 | Deep learning<br>Machine learning<br>Natural language processing<br>Neural network<br>Recommendation algorithm | Artificial intelligence related algorithms |
| N13 | Object detection<br>Identification tracking<br>Image<br>Video<br>Division | Computer vision industrial automation system |
| N14 | Signal simulation<br>Digital signal processing<br>Radar | Digital signal processing and simulation |
| N15 | English<br>File<br>Fast reading | Foreign language ability |
| | Paper publication | Academic achievements |

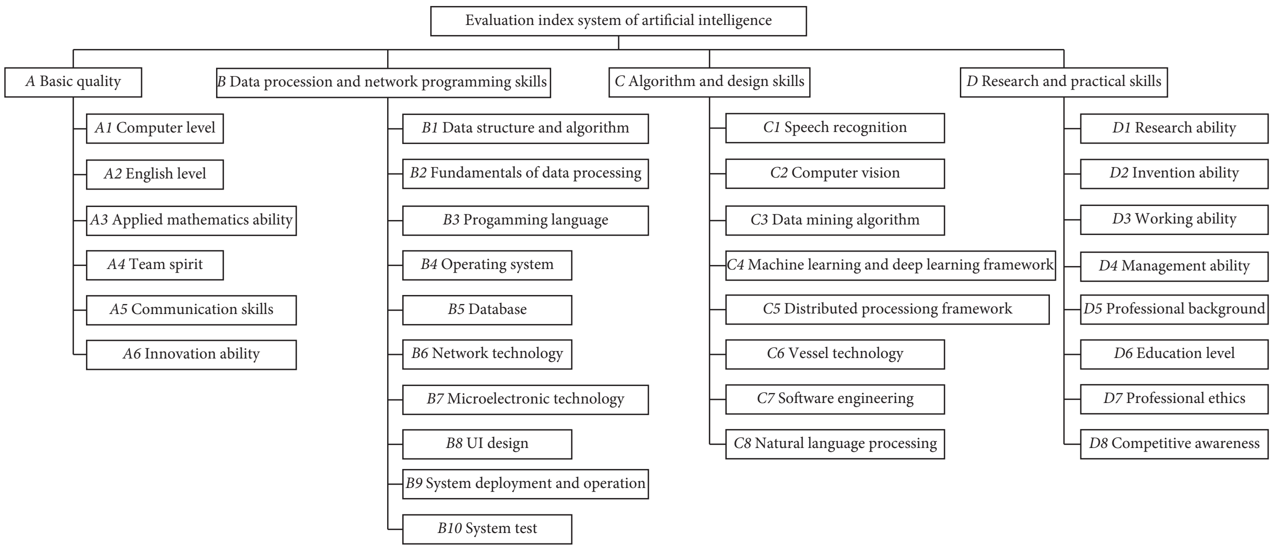

Figure 7: Construction of the preliminary evaluation index system of artificial intelligence professional ability.

were distributed, and 152 valid questionnaires were left after eliminating the questionnaires that were completed too carelessly, with an effective recovery rate of 95%. The Cronbach's $\alpha$ coefficient in the reliability test result of the questionnaire was 0.964, which is greater than 0.8; that is, the reliability of the questionnaire is sufficiently high. The *KMO* value of the validity test was 0.881, greater than 0.8, the chi-square of Bartlett's test of sphericity was 4867.51, and the corresponding $p$ value was 0, less than 0.05, indicating that the data are suitable for factor analysis. The dimensionality reduction results of factor analysis are shown in Table 3, and the accumulative contribution rate is 70.813, indicating that most of the information on the variables is well explained.

According to the factor analysis results of second-level indicators $B1$, $B2$, and $B3$, it is suggested to classify them into the category of first-level indicator $A$. After adjusting the membership of indicators, we modify the names of first-level indicator $A$ and first-level indicator $B$ as "*A* Basic artificial intelligence vocational skills" and "*B* Database and network skills." In the second round of the Delphi process, 21 experts, whose authority value was greater than 3 in the first round were selected to form a new group, and the overall authority value increased to 3.95. The importance scoring results obtained in the first round of correspondence were attached to the questionnaire to achieve the effect that the opinions of experts were consistent. After the second round of Delphi expert consultation, the value range of the variation coefficient of each index changed from 0.135 to 0.324 in the first round to 0.092~0.220. The maximum value of the coefficient of variation was less than 0.25, and the index coordination coefficient increased from 0.129 to 0.346. This indicated a high degree of coordination of expert opinions. Therefore, the Delphi consultation was terminated. We established the final artificial intelligence professional ability evaluation index system and the connotation of each index, as shown in Table 4.

Table 3: Factor analysis results of the artificial intelligence professional ability evaluation index.

| Code | Extracted principal components | | Code | Extracted principal components | |
|---|---|---|---|---|---|
| | 1 | 2 | | 3 | 4 |
| A1 | 0.678 | | C1 | 0.550 | |
| A2 | 0.536 | | C2 | 0.714 | |
| A3 | 0.696 | | C3 | 0.536 | |
| A4 | 0.657 | | C4 | 0.762 | |
| A5 | 0.623 | | C5 | 0.736 | |
| A6 | 0.571 | | C6 | 0.732 | |
| B1 | 0.738 | | C7 | 0.726 | |
| B2 | 0.717 | | C8 | 0.700 | |
| B3 | 0.691 | | D1 | | 0.669 |
| B4 | | 0.708 | D2 | | 0.686 |
| B5 | | 0.552 | D3 | | 0.774 |
| B6 | | 0.783 | D4 | | 0.684 |
| B7 | | 0.808 | D5 | | 0.745 |
| B8 | | 0.750 | D6 | | 0.694 |
| | | | D7 | | 0.701 |
| | | | D8 | | 0.664 |

## 6. Determination of Weight

*6.1. Constructing the Intuitionistic Fuzzy Judgement Matrix.* We make a pairwise comparison of the relative importance of the four first-level indicators of the constructed index system and use the same method to make a pairwise comparison of the second-level indicators under each first-level indicator. Based on this, we establish the intuitionistic fuzzy judgement matrix $R = (r_{ij})_{n\times n}$ according to the standards in Table 5. The symbols $i$ and $j$ represent the rows and columns of the judgement matrix, respectively. Where $r_{ij} = (\mu_{ij}, \nu_{ij})$ $(i, j = 1, 2, 3, \ldots, n)$, $\mu_{ij}$ indicates the degree to which the $i$-th indicator is more important than the $j$-th indicator, that is, the degree of membership. The symbol $\nu_{ij}$ indicates the degree to which the $j$-th index is more important than the $i$-th index, that is, the

Table 4: Evaluation index system and connotation of artificial intelligence professional ability.

| First-level index | Second-level index | Standard and connotation of each index |
|---|---|---|
| *A* basic artificial intelligence vocational skills | *A*1 computer level | The ability to use computers to deal with general problems |
| | *A*2 English level | English listening, speaking, reading and writing ability, especially foreign literature reading and learning ability |
| | *A*3 applied mathematics ability | Ability to model and solve problems using mathematical methods |
| | *A*4 team spirit | Have the overall concept, participate in team cooperation and jointly complete the teamwork objectives |
| | *A*5 communication skills | Be able to communicate effectively with internal and cross teams, respond to the needs of other types of post problems, and realize the business landing of artificial intelligence application scenarios |
| | *A*6 innovation ability | Can solve more complex application problems through reasonable combination, transformation, and innovation of relevant algorithm models |
| | *A*7 data structure and algorithm | Master basic algorithms such as recursion, sorting, and binary search, and use data structures flexibly |
| | *A*8 fundamentals of data processing | Have data processing ability, such as text, image, web page, and other data import, processing, transformation, etc. |
| | *A*9 programing language | Master C/C++, Python, java, and other programming languages |
| *B* database and network skills | *B*1 operating system | Master the development environment of mainstream operating systems such as MAC, Linux, and Windows |
| | *B*2 database | Master MySQL, Oracle, SQL Server, and other mainstream databases |
| | *B*3 network technology | Master the network configuration and application of switches and servers |
| | *B*4 electronic technology | Master the technology related to hardware design and development such as the artificial intelligence chip |
| | *B*5 UI design | Design and development of interactive interface of artificial intelligence equipment |
| *C* algorithm and design skills | *C*1 speech recognition | Master deep learning algorithms and models related to speech recognition |
| | *C*2 computer vision | Master computer vision-related problems and solutions, such as detection, tracking, classification, semantic segmentation, reinforcement learning, 3D vision and image processing, and master OpenCV, Halcon, VisionPro, and other machine vision development technologies |
| | *C*3 data mining algorithm | Master the principles of common data mining algorithms such as logistic regression and decision tree, and can apply them to practical scenarios |
| | *C*4 machine learning and deep learning framework | Master machine learning algorithms and mainstream deep learning frameworks such as Caffe, TensorFlow, and PyTorch |
| | *C*5 distributed processing framework | Master common distributed open-source frameworks such as Hadoop, Spark, and Storm |
| | *C*6 Vessel technology | Master Docker, K8S, Mesos, and other container technologies |
| | *C*7 software engineering | Master software design tools and be able to manage software engineering |
| | *C*8 natural language processing | Master deep learning algorithms and models related to natural language processing |
| *D* research and practical skills | *D*1 research ability | Publish artificial intelligence-related papers in core journals or international conferences |
| | *D*2 invention ability | Patent achievements related to artificial intelligence as the main inventor |
| | *D*3 Working ability | Working years and positions related to artificial intelligence |
| | *D*4 management ability | Experience in the development and implementation of AI products and projects as the main person in charge |
| | *D*5 professional background | Professional background requirements related to artificial intelligence |
| | *D*6 education level | Educational level requirements of artificial intelligence-related majors |
| | *D*7 professional ethics | Abide by laws and industrial ethics, and be vigilant against technical risks and privacy security |
| | *D*8 Competitive awareness | The ability to use computers to deal with general problems |

nonmembership degree. $\pi_{ij}$ represents the degree of hesitation, $\pi_{ij} = 1 - \mu_{ij} - \nu_{ij}$.

The scoring results of multiple experts are collected through the intuitionistic fuzzy weighted average operator, IFWA. A set of intuitionistic fuzzy numbers is set as $r_i = (\mu_i, \nu_i)$ $(i = 1, 2, \ldots)$, $IFWA{:}\Theta^n \longrightarrow \Theta$, if $IFWA_\omega(r_1, r_2, \ldots, r_n) = \omega_1 r_1 \oplus \omega_2 r_2 \oplus \ldots \oplus \omega_n r_n$. In addition, $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ is the weight vector of $r_i$ $(i = 1, 2, \ldots, n)$, and its value is the normalized authority value of experts participating in intuitionistic fuzzy judgment research, that is, $\sum_{j=1}^{n} \omega_j = 1$. The operation of the intuitionistic fuzzy information set follows the following rules:

Table 5: Comparison between experts' preference and intuitionistic fuzzy numbers.

| Experts' preference | Intuitionistic fuzzy numbers |
|---|---|
| Compared with the two indicators, $i$ is extremely more important than $j$ | (0.90, 0.10, 0.00) |
| Compared with the two indicators, $i$ is strongly more important than $j$ | (0.80, 0.15, 0.05) |
| Compared with the two indicators, $i$ is obviously more important than $j$ | (0.70, 0.20, 0.10) |
| Compared with the two indicators, $i$ is moderately more important than $j$ | (0.60, 0.25, 0.15) |
| Compared with the two indicators, $i$ and $j$ are equally important | (0.50, 0.30, 0.20) |
| Compared with the two indicators, $j$ is moderately more important than $i$ | (0.40, 0.45, 0.15) |
| Compared with the two indicators, $j$ is obviously more important than $i$ | (0.30, 0.60, 0.10) |
| Compared with the two indicators, $j$ is strongly more important than $i$ | (0.20, 0.75, 0.05) |
| Compared with the two indicators, $j$ is extremely more important than $i$ | (0.10, 0.90, 0.00) |

Table 6: Intuitionistic fuzzy judgement matrix (taking first-level index as an example).

| Judgement matrix | Intuitionistic fuzzy set | | | |
|---|---|---|---|---|
| | (0.5, 0.5) | (0.4310, 0.3820) | (0.5152, 0.4321) | (0.3768, 0.5102) |
| $X$ | (0.3820, 0.4310) | (0.5, 0.5) | (0.4166, 0.4553) | (0.4830, 0.4040) |
| | (0.4321, 0.5152) | (0.4553, 0.4166) | (0.5, 0.5) | (0.4633, 0.3952) |
| | (0.5102, 0.3768) | (0.4040, 0.4830) | (0.3952, 0.4633) | (0.5, 0.5) |

$$\alpha_1 \oplus \alpha_2 = \left(\mu_{\alpha_1} + \mu_{\alpha_2} - \mu_{\alpha_1} * \mu_{\alpha_2},\ \nu_{\alpha_1} * \nu_{\alpha_2}\right), \tag{6}$$

$$\alpha_1 \otimes \alpha_2 = \left(\mu_{\alpha_1} * \mu_{\alpha_2},\ \nu_{\alpha_1} + \nu_{\alpha_2} - \nu_{\alpha_1} * \nu_{\alpha_2}\right), \tag{7}$$

$$\lambda\alpha_1 = \left(1 - (1-\mu_1)^{\lambda},\ \nu_1^{\lambda}\right), \tag{8}$$

$$\alpha_1^{\lambda} = \left(\mu_1^{\lambda},\ 1 - (1-\nu_1)^{\lambda}\right). \tag{9}$$

This research used the senior management of artificial intelligence companies established for more than 10 years, professors and associate professors of artificial intelligence-related majors in higher vocational colleges and universities directly under the Ministry of Education, and a total of 5 experts. They scored the relative importance of indicators at all levels of the constructed system. The questionnaire also required experts to judge their familiarity with each index and indicate the judgment basis of relative importance to quantify the authority of experts. The authority value $C_r$ is normalized to obtain the expert weight vector $\omega = (0.19, 0.19, 0.22, 0.21,$ and $0.19)$ $T$. The intuitionistic fuzzy weighted average operator $\mathrm{IFWA}_{\omega}(r_1, r_2, \ldots, r_6) = 0.19r_1 \oplus 0.19r_2 \oplus\ 0.22r_3 \oplus 0.21r_4 \oplus 0.19r_5$. Combined with Formulas (6) and (8), the intuitionistic fuzzy judgment matrix of indices at all levels is obtained. The relative importance of the first-level index to the total index is taken as an example, and the intuitionistic fuzzy judgment matrix $X$ is shown in Table 6.

*6.2. Consistency Check.* The consistency check can be used to establish whether there is conflict in the evaluation of the relative importance of indicators by expert;ls. If the consistency check fails, formula iteration can be carried out by setting parameters without the second scoring by experts. The formula of the consistency check is [51]:

$$d(\overline{R}, R) = \frac{1}{2(n-1)(n-2)} \cdot \sum_{i=1}^{n}\sum_{j=1}^{n}\left(\left|\overline{\mu}_{ij} - \mu_{ij}\right| + \left|\overline{\nu}_{ij} - \nu_{ij}\right| + \left|\overline{\pi}_{ij} - \pi_{ij}\right|\right), \tag{10}$$

where $R$ represents the intuitionistic fuzzy judgement matrix $R = (r_{ij})_{n\times n}$, $\overline{R}$ represents the intuitionistic fuzzy consistency judgement matrix $\overline{R} = (\overline{r}_{ij})_{n\times n}$, and the calculation formula of $\overline{R}$ is [50]:

(1) When $j > i+1$, let $\overline{r}_{ij} = (\overline{\mu}_{\mathrm{ij}}, \overline{\nu}_{ij})$, where:

$$\overline{\mu}_{ij} = \frac{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\mu_{it}\mu_{tj}}}{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\mu_{it}\mu_{tj}} + \sqrt[j-i-1]{\prod_{t=i+1}^{j-1}(1-\mu_{it})(1-\mu_{tj})}},\ j > i+1,$$
$$\overline{\nu}_{ij} = \frac{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\nu_{it}\nu_{tj}}}{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\nu_{it}\nu_{tj}} + \sqrt[j-i-1]{\prod_{t=i+1}^{j-1}(1-\nu_{it})(1-\nu_{tj})}},\ j > i+1. \tag{11}$$

(2) When $j = i+1$, let $\overline{r}_{ij} = (\mu_{ij}, \nu_{ij})$,

(3) When $j < i$, let $\overline{r}_{ij} = (\overline{\nu}_{ji}, \overline{\mu}_{ji})$.

We substitute the calculated intuitionistic fuzzy consistency judgment matrix $\overline{R}$ into (10) for consistency check calculation. If the calculated $d(R, R) < 0.1$, the consistency check passes. If $\overline{R}$ fails to pass the consistency check, the iterative parameter $\sigma$ is introduced. We then adjust the value of the iterative parameters and calculate and correct the intuitionistic fuzzy consistency judgment matrix according to Formula [50]:

$$\widetilde{\mu}_{ij}=\frac{\left(\mu_{ij}\right)^{1-\sigma}\left(\overline{\mu}_{ij}\right)^{\sigma}}{\left(\mu_{ij}\right)^{1-\sigma}\left(\overline{\mu}_{ij}\right)^{\sigma}+\left(1-\mu_{ij}\right)^{1-\sigma}\left(1-\overline{\mu}_{ij}\right)^{\sigma}},\quad i,j=1,2\ldots n, \tag{12}$$

$$\widetilde{\nu}_{ij}=\frac{\left(\nu_{ij}\right)^{1-\sigma}\left(\overline{\nu}_{ij}\right)^{\sigma}}{\left(\nu_{ij}\right)^{1-\sigma}\left(\overline{\nu}_{ij}\right)^{\sigma}+\left(1-\nu_{ij}\right)^{1-\sigma}\left(1-\overline{\nu}_{ij}\right)^{\sigma}}i,\quad j=1,2\ldots n. \tag{13}$$

The changed intuitionistic fuzzy consistency judgment matrix $\widetilde{R}=(\widetilde{r}_{ij})_{n\times n}$, where $\widetilde{r}_{ij}=(\widetilde{\mu}_{ij},\widetilde{\nu}_{ij})$, is substituted into Formula (14) for the calculation check until the consistency check is passed.

$$d(\bar{R},\widetilde{R})=\frac{1}{2(n-1)(n-2)}\cdot\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\left|\widetilde{\mu}_{ij}-\bar{\mu}_{ij}\right|+\left|\widetilde{\nu}_{ij}-\bar{\nu}_{ij}\right|+\left|\widetilde{\pi}_{ij}-\bar{\pi}_{ij}\right|\right). \tag{14}$$

The consistency of five intuitionistic fuzzy judgment matrices is checked according to Formula (10). For the judgment matrix $R$ with $d(\overline{R},R)>0.1$, the iterative parameter $\sigma_A\in(0,1)$ is introduced, taking 0.1 as the starting point and a step size of 0.1. According to the iterative test of Formulas (13) to (15), the adjusted value is calculated until $d(\bar{R},\widetilde{R})<0.1$. The results of the parameter adjustment and consistency check are shown in Table 7.

Taking the relative importance of the first-level index to the total index as an example, the adjusted and corrected intuitionistic fuzzy judgment matrix $\widetilde{X}$ is shown in Table 8.

*6.3. Weight Calculation.* The index weight value of each level is calculated by the modified intuitionistic fuzzy consistency judgment matrix that has passed the consistency check, and the calculation formula is [50]:

$$\omega_i=\left(\frac{\sum_{j=1}^{n}\mu_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(1-\nu_{ij}\right)},1-\frac{\sum_{j=1}^{n}\left(1-\nu_{ij}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\mu_{ij}}\right)i,\quad j=1,2\ldots n. \tag{15}$$

The calculated weights are two-dimensional. To meet the more intuitive evaluation requirements, the two-dimensional index weights need to be fuzzily transformed from a vague set to a fuzzy set [52].

Let $U$ be a universe, $A$ be a vague set in $U$, and $A=\{<t_A(x), f_A(x), \pi_A(x)>|x\in U\}\in V(U)$. Then, $A^{(n)}=\{<t_A{}^{(n)}(x), f_A{}^{(n)}(x), \pi_A{}^{(n)}(x)>|x\in X\}$ is called the $n$-th transformation from $A$ to the fuzzy set. If $t_A(x)$ and $f_A(x)$ are not all 0, then when $n\longrightarrow\infty$, the limit state of $A$ transformation to a fuzzy set is:

Table 7: Parameter adjustment and consistency check results.

| Judgement matrix | $d(\overline{R},R)$ | Adjust parameters $\sigma$ | $d(\overline{R},\widetilde{R})$ |
|---|---|---|---|
| $X$ | 0.2012 | 0.5 | 0.098 |
| $A$ | 0.1818 | 0.5 | 0.0849 |
| $B$ | 0.1394 | 0.3 | 0.0929 |
| $C$ | 0.1538 | 0.4 | 0.0879 |
| $D$ | 0.1390 | 0.3 | 0.0891 |

Table 8: Intuitionistic fuzzy judgement matrix after adjustment and correction (taking first-level index as an example).

| Judgement matrix | Intuitionistic fuzzy set | | | |
|---|---|---|---|---|
| $\widetilde{X}$ | (0.5, 0.5) | (0.4310, 0.3820) | (0.4310, 0.3854) | (0.4111, 0.4081) |
| | (0.3820, 0.4310) | (0.5, 0.5) | (0.4166, 0.4553) | (0.4315, 0.3783) |
| | (0.3854, 0.4312) | (0.4553, 0.4166) | (0.5, 0.5) | (0.4633, 0.3952) |
| | (0.4081, 0.4111) | (0.3783, 0.4315) | (0.3952, 0.4633) | (0.5, 0.5) |

$$A^{(\infty)}=\left\{<t_A^{(\infty)}(x), f_A^{(\infty)}(x),\pi_A^{(\infty)}(x)>|x\in X\right\}, \tag{16}$$

$$t_A^{(\infty)}(x)=t_A(x)\prod_{k=1}^{\infty}\left(1+\pi_A(x)\right)^{2^{k-1}}=\frac{t_A(x)}{1-\pi_A(x)}=\frac{t_A(x)}{t_A(x)+f_A(x)}, \tag{17}$$

$$f_A^{(\infty)}(x)=f_A(x)\prod_{k=1}^{\infty}\left(1+\pi_A(x)\right)^{2^{k-1}}=\frac{f_A(x)}{1-\pi_A(x)}=\frac{f_A(x)}{t_A(x)+f_A(x)},\quad \pi_A^{(\infty)}(x)=0. \tag{18}$$

At this time, $t_A{}^{(\infty)}(x)+f_A{}^{(\infty)}(x)=1$, and $A^{(\infty)}$ is a fuzzy set. Then, the transformed fuzzy set of vague set $A$ is $A^F(x)=\{<x, A^F(x)>x\in U\}=t_A{}^{(\infty)}(x)$. We normalize all $A^F(x)$ at the same level to obtain the final weight of indicators at each level.

After the five modified intuitionistic fuzzy matrices passing the consistency check are calculated by Formula (15) to aggregate the weights, the fuzzy set is transformed by Formula (17), the two-dimensional weights are mapped to one-dimensional weights, and the obtained $A^F(x)$ is normalized to obtain the one-dimensional comprehensive weights of indicators at all levels. The weight calculation results are shown in Table 9.

*6.4. Analysis of the Results.* From the weight assignment results, it can be seen that the weights of the four first-level indicators are almost the same. However, the weight of "$C$ algorithm and design skills" is 0.2564, which is relatively

Table 9: Weight of artificial intelligence professional ability evaluation index.

| First-level index | Second-level index | Final weight of the second-level index |
|---|---|---|
| *A* (0.1968, 0.6674) 0.2559 | *A*1 (0.1012, 0.8164) 0.1431 | 0.0366 |
| | *A*2 (0.0734, 0.8554) 0.1025 | 0.0262 |
| | *A*3 (0.1028, 0.8158) 0.1452 | 0.0372 |
| | *A*4 (0.0689, 0.8566) 0.0966 | 0.0247 |
| | *A*5 (0.0685, 0.8565) 0.0961 | 0.0246 |
| | *A*6 (0.0760, 0.8455) 0.1070 | 0.0274 |
| | *A*7 (0.0825, 0.8356) 0.1166 | 0.0298 |
| | *A*8 (0.0657, 0.8618) 0.0919 | 0.0235 |
| | *A*9 (0.0716, 0.8489) 0.1009 | 0.0258 |
| *B* (0.1920, 0.6801) 0.2474 | *B*1 (0.1788, 0.7155) 0.2319 | 0.0574 |
| | *B*2 (0.2010, 0.6886) 0.2621 | 0.0648 |
| | *B*3 (0.1395, 0.7561) 0.1807 | 0.0447 |
| | *B*4 (0.1350, 0.7611) 0.1747 | 0.0432 |
| | *B*5 (0.1166, 0.7816) 0.1506 | 0.0373 |
| *C* (0.2002, 0.6771) 0.2564 | *C*1 (0.0952, 0.8132) 0.1332 | 0.0342 |
| | *C*2 (0.0925, 0.8211) 0.1287 | 0.0330 |
| | *C*3 (0.1158, 0.7940) 0.1618 | 0.0415 |
| | *C*4 (0.1164, 0.7916) 0.1630 | 0.0418 |
| | *C*5 (0.0925, 0.8242) 0.1283 | 0.0329 |
| | *C*6 (0.0733, 0.8522) 0.1007 | 0.0258 |
| | *C*7 (0.0632, 0.8653) 0.0865 | 0.0222 |
| | *C*8 (0.0708, 0.8487) 0.0979 | 0.0251 |
| *D* (0.1866, 0.6860) 0.2403 | *D*1 (0.1440, 0.7793) 0.1898 | 0.0456 |
| | *D*2 (0.1275, 0.7996) 0.1674 | 0.0402 |
| | *D*3 (0.0971, 0.8313) 0.1272 | 0.0306 |
| | *D*4 (0.0941, 0.8358) 0.1232 | 0.0296 |
| | *D*5 (0.0898, 0.8426) 0.1172 | 0.0281 |
| | *D*6 (0.0901, 0.8403) 0.1179 | 0.0283 |
| | *D*7 (0.0675, 0.8728) 0.0874 | 0.0210 |
| | *D*8 (0.0542, 0.8895) 0.0699 | 0.0168 |

high. This shows that as one of the three cornerstones of artificial intelligence, the mastery of algorithms is an important standard for investigating the professional ability of artificial intelligence talent, and is an important link between the college training plan and industry talent development. The second is "*A* Basic artificial intelligence vocational skills," with a weight of 0.2559. The basic vocational skills of artificial intelligence are the basic requirements for engaging in artificial intelligence-related work, which is composed of general basic skills and basic data processing and programming skills of front-line employees in various industries. "*B* Database and network skills" is the third place, with a weight of 0.2474. Database and network skills are professional skills and knowledge highly related to artificial intelligence. Databases store massive data in computers to complete the management and sharing of data, while computer networks can establish connections between decentralized independent computers to achieve the purpose of information resource sharing. As a high-tech industry, artificial intelligence attracts a considerable number of young practitioners. Therefore, the requirements for practical experience are not strict, and the professional background is highly inclusive. The weight value of "*D* Research and practical skills" is thus lower, which is 0.2403.

Under the first-level indicator "*A* Basic artificial intelligence vocational skills," the weight of applied mathematics ability and computer level far exceeds that of other second-level indicators, followed by the data structure, algorithm, and innovation ability. Under "*B* Database and network skills," mastering the development environment of the mainstream database and the mainstream operating system is also the most important indicator. The high professional threshold of the artificial intelligence industry makes the evaluation of the basic quality and skills of talent focus on the professional skills and knowledge of the industry and requires innovation ability on this basis. The three cornerstones of artificial intelligence are algorithms, data, and computing power. Data mining, machine learning, and deep learning algorithms are the fundamental ways to realize artificial intelligence, simulate human learning behavior, and endow computers with intelligence. Therefore, in the first-level index "*C* Algorithm and design skills," mastering the data mining algorithms, machine learning, and deep learning frameworks have a great impact on the evaluation results of professional ability, while speech recognition and computer vision are the most popular practical application scenarios of artificial intelligence in recent years. These are not only the hot topics of algorithm research in colleges and universities but also the technical opportunity directions of industry development. They also have a high weight in the evaluation system. The second-level index weight data under "*D* Research and practical skills" shows that research and invention ability is also an important evaluation dimension, which reflects the employees' research depth and innovation consciousness.

## 7. Conclusion

Based on the mining and content analysis of the recruitment text of artificial intelligence posts on a recruitment website, this paper extracts five main types of artificial intelligence posts: basic application posts, technical support posts, application development posts, algorithm research posts, and senior R&D posts. Based on the work responsibilities and corresponding ability needs of various posts, combined with the talent training plan of colleges and universities obtained from expert consultation and literature research, a multidimensional evaluation index system of the professional ability of artificial intelligence talent is constructed. Then, the index weights at all levels are calculated according to the intuitive fuzzy judgment of experts under the two backgrounds of "industry" and "education." By analyzing the index weight calculation results of the intuitive fuzzy analytic hierarchy process in Section 6.4, it is found that the weight of the "C Algorithm and design skills" is 0.2564, which is the highest among the four first-level indicators. This shows that the industry and education expert groups surveyed in this study agree that the algorithms and design skills from the perspective of the integration of industry and education are the most important evaluation dimension of the professional ability of artificial intelligence talent. Talent is also required to master data mining and machine learning and deep learning algorithms and have the ability to solve practical problems of computer vision and speech recognition. On the one hand, in terms of the need for learning and innovation in colleges and universities, the mastery and research of algorithms is the cornerstone of the continuous updating of AI's cutting-edge technology. On the other hand, the design skills of AI talent are an important driving force for the implementation of cutting-edge research on algorithms and the continuous development of the AI industry. In addition, the basic abilities of the evaluated object are of great concern. Among the basic abilities, professional skills such as applied mathematics, computers, data structures, and algorithms are more important, and the basic quality is mainly innovation ability. The weight of the database and network skill dimension ranks third, and talent is mainly required to be familiar with the mainstream database and mainstream operating system development environment. The last is the dimension of research and practical skills. The results of papers published in core journals or international conferences and artificial intelligence patents are all bonus items of professional ability evaluation.

Human-job match theory points out that human personality differences are common, and any individual has his or her own characteristics. The fundamental problem is how to put talent in appropriate positions to give full play to their maximum effectiveness. The final analysis is to overcome the problem of information asymmetry between positions and the workforce. The integration of industry and education is an effective way to solve the serious problem of talent training and demand mismatch. In the process of talent training, the cultivation method of industry and education integration takes projects as the link and deepens the cooperation between schools and enterprises, which is an effective way to cultivate high-level applied talent. In addition to artificial intelligence posts, the professional ability evaluation of various industries in urgent need of applied talent is applicable to the perspective of integration of industry and education, especially in industries that have high requirements for the technical level and innovation consciousness of employees. This paper studies the vocational ability evaluation system based on artificial intelligence from the perspective of the integration of production and education, which has a certain reference significance for the vocational ability evaluation of applied talent in other industries in the future.

Based on the abovementioned results, we believe that strengthening the integration of industry and education and promoting the training of artificial intelligence talent is still an effective means to comply with the rapid development of artificial intelligence skills and alleviate the contradiction between talent supply and industry demand. The selection of indicators in this study is based on the demanded text of artificial intelligence talent, combined with the actual business scenarios of the industry and theoretical research in the literature. In the process of index establishment and weight calculation, the cognition of experts from both "industry" and "education" was consulted and integrated. The integration of these factors could lead to a more multidimensional and unified evaluation system and a beneficial supplement to ease the lack of talent skill certification in today's artificial intelligence industry. However, the evaluation index system is only one way to test the professional talent ability. If the talent training of the artificial intelligence industry wants to achieve the "integration of industry and education" and shorten the distance between higher education and the actual needs of industry development, it is more important to pay attention to the mutual penetration and support of the roles of universities and industry. In this context, one could consider a cooperative teaching mode between schools and enterprises, encourage innovative research based on enterprise R&D projects, and provide more practical opportunities in talent education. One could also explore the training mode of "artificial intelligence +" compound talent and implement the training strategy of professional differentiation to promote an effective connection between the paths of talent education and industry development.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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