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Exploration of the Path of Cultivating Employability of College Students in the Context of Artificial Intelligence Era

Wen Zou[1,*]

[1] Zhengzhou Technology and Business University, Zhengzhou, Henan, 451400, China

SUMMARY: *Under the growing demands of employment-based education, developing employability skills is the main goal of many higher education institutions nowadays. In order to find ways to develop university students' employability skills, this paper focuses on senior undergraduate students at University A. On the basis of the USEM model, an evaluation system for employability skills is established. By using the method of least squares, the weights of the evaluation indicators are calculated, thus allowing to conduct the comprehensive evaluation of the employability skills of the sampled students. Besides, an integrated model with Improved Random Forest and Deep Belief Network (DBN) is suggested for predicting the employment result of students. Through a comparison of feature importance, important factors that affect the employment of university students are selected.*

KEYWORDS: *USEM model; Least Squares Method; Random Forest; Deep Belief Network; Employment Competency*

1 Introduction

Due to the fast development of artificial intelligence, smart devices and products are invading and being utilized by all areas of life. The involvement of humans in activities related to knowledge generation is decreasing; the substitute ability of many traditional professions is becoming stronger, and demands on talents keep increasing [1-3]. In different industries, the predictability, measurability, and efficiency of artificial intelligence contribute to a huge increase in individual efficiency, while changing traditional methods of manufacturing. Repetitive cognitive work and mechanical labor are now being substituted [4-6]. At the same time, technological advances make the trend toward comprehensive development move faster, which forces universities to search for reforms in their institutions, develop innovative teaching models, and pay special attention to interdisciplinary knowledge. This approach aims to deliver high-quality talent to society, gradually increasing the proportion of innovative and multidisciplinary professionals within the workforce structure [7-10]. To meet contemporary talent development needs, policy guidance is progressively exploring the cultivation of "AI+X" cross-disciplinary professionals, emphasizing the integration of different disciplines with AI-focused interdisciplinary education [11-13]. Against this backdrop, teaching reforms oriented toward enhancing students' employability have become imperative for higher education institutions.

In recent years, higher education institutions have prioritized market demand as a guiding principle, focusing on enhancing students' employability as the core educational objective. They have deepened their understanding of professional competency requirements, advanced

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*zouwen2025@126.com
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academic supervision-driven initiatives, strengthened employment guidance-driven approaches, and implemented entrepreneurship-driven programs [14-16]. After constant adjustments to the plans for the growth and development of professional talents and course outlines, they have created a practical teaching system that puts emphasis on the employability of students. The four-pronged teaching system has been explored by combining course modularization, systematic technical training, project competition and practical experience. Moreover, a series of university-enterprise cooperation involving many parties has been facilitated to organize participation from the students to give new ideas about fostering the employability of students [17-20]. In the light of the age of artificial intelligence, there are some problems need to be solved. Specifically, how to improve the professional competency of students, adapt university students to the changed needs of the market and foster innovative abilities and professional skills.

Firstly, in this paper, we will use the USEM model to create an evaluation system of university students' employability. Four indicators include subject comprehension (U), comprehensive skills (S), personal endowment (E), and metacognition (M). Besides, each of them contains 20 sub-indicators like learning attitudes and discipline knowledge. According to the proposed evaluation model, the weights of each indicator are gained through combining the objective and subjective weights which were got by using the improved G1 method and CRITIC method with the least squares method. Based on the weight above, the employment competency score of each student is gained, completing the evaluation process for university students' employment capability. Secondly, we propose a hybrid deep learning model by combining random forest and deep belief network (DBN) to predict student employment. By utilizing DBN to extract features in advance and fine-tune afterwards, the hybrid deep learning model can predict student employment precisely. Thirdly, by comparing the importance of the selected features, this paper will evaluate the role of curriculum modularization in cultivating student employment capability. Based on the results of evaluating student employment capability and predicting student employment outcome, we put forward suggestions for university students' employability improvement.

2 Study Design

Under the background of artificial intelligence, the employment environment becomes more and more difficult. Society and companies have higher expectations of talents and make higher demands on the employment capability of the college students. In order to solve the employment problems of the university students under complex circumstances, this paper proposes a model that gives weightings subjectively and objectively to the factors affecting university students' employment by using the least square method. The employment capability evaluation model is constructed to comprehensively evaluate the employment capability of the university students. Besides, a new method combining the improved random forest (RF) model and deep belief network (DBN) is used to predict employment capability. According to the above two models, the cultivation path of university students’ employment capability is proposed.

2.1 Research Objectives

Through an analysis of the assessment of their job readiness and career projections, this study intends to investigate more focused approaches to developing students' employability skills, thus offering more guidance for universities and students regarding career preparation in the artificial intelligence age.

2.2 Research Subjects

This study focuses on 1,216 senior students from University A of the Class of 2025 in a specific province of China. The source of this research data is students' information gathered during the National Engineering Education Accreditation in China. This data set is made up of various parts, such as college records, questionnaires, and scores in comprehensive assessments. Student data include student number, names of courses, credit, grade of regular coursework, midterm exam score, final exam score, laboratory score, and score of comprehensive evaluation.

2.3 Research Methods

The main research methods used in this study include the following:

2.3.1 Literature Review Method

The literature review method is defined as a research methodology that relies on extensive collection and thorough examination of theoretical and documentary information pertinent to a topic, after which they are summarized and synthesized to establish the theoretical basis of the research topic. It is accomplished by the collection and analysis of data and documents obtained from online databases, reputable domestic and foreign periodicals and books, and statistical yearbooks and official notices released by relevant government websites.

2.3.2 Statistical Analysis Method

Statistical analysis is defined as a research approach which uses some statistical methods for the study of macro- or micro-level data gathered. The goals of this technique include finding relationships between indicators used, detecting hidden structures in the data set, and making predictions about future trends.

2.3.3 USEM Model

Different models of college students' employability have been developed from different angles, including their competences, such as two-, three-, four-, and multidimensional models. One of these models – USEM, seems to be the most characteristic and typical one, which is shown in Figure 1. This model includes four interrelated variables, namely, disciplinary knowledge, skills, personality factors, and metacognitive capabilities. It should be noted that all of the mentioned components form a complex synergy and determine an individual's employability. It provides a crucial theoretical foundation and analytical framework for employment competency research, offering significant reference value and guidance for evaluating and enhancing college students' employment capabilities.

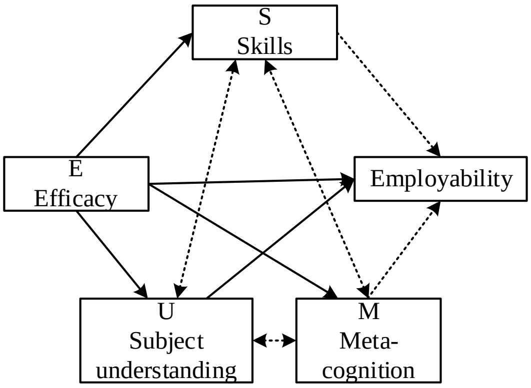

Figure 1: USEM model

2.3.4 College Student Employment Competency Evaluation Model

1) G1 Sequence Method

The G1 Sequence Method is an improved subjective weighting technique for the Analytic Hierarchy Process (AHP). It constructs a judgment matrix using the scaling extension method, eliminating the need for complex consistency tests. Its fundamental principles are as follows: First, rank the n indicators $(x_1, x_2, \cdots, x_n)$ to be evaluated in descending order based on expert experience and user requirements, assuming $x_1 > x_2 > \cdots > x_n$; Next, compare the importance of x_j with that of x_{j+1} to obtain the scaling value t_j .

By comparing each indicator with others, we obtain a judgment matrix $R = [r_{kj}]$ composed of scale values. The judgment matrix R satisfies the following properties:

(1) r_{kj} represents the scaled value obtained by comparing the k th criterion with the j th criterion, where $k, j = 1, 2, \cdots, n$;

(2) $r_{kj} = 1 / r_{jk}$;

(3) $r_{ij} = 1$;

(4) $r_{kj} = r_{kt} \cdot r_{ij}$ where $k = 1, 2, \cdots, n$.

The calculation formula is as follows:

$$R = \begin{bmatrix} 1 & t_1 & t_1 t_2 & \cdots & t_1 t_2 \cdots t_{n-1} \\ 1/t_1 & 1 & t_2 & \cdots & t_2 t_3 \cdots t_{n-1} \\ 1/t_1 t_2 & 1/t_2 & 1 & \cdots & t_3 t_4 \cdots t_{n-1} \\ \vdots & \vdots & \vdots & & \vdots \\ 1/t_1 t_2 \cdots t_{n-1} & 1/t_2 t_3 \cdots t_{n-1} & 1/t_3 t_4 \cdots t_{n-1} & \cdots & 1 \end{bmatrix} \tag{1}$$

It follows that the consistency test for matrix R is satisfied, and reasonable subjective weights can be obtained without further consistency verification. The subjective weights for each indicator are as follows:

$$\alpha_j = \frac{\sqrt[n]{\prod_{i=1}^{n} r_{ij}}}{\sum_{j=1}^{n} \sqrt[n]{\prod_{i=1}^{n} r_{ij}}} \tag{2}$$

2) CRITIC Weighting Method

The CRITIC method is an objective weighting technique based on indicator data. It primarily relies on the comparative strength and conflict between data points [21]. The comparative strength is expressed as the standard deviation, indicating the degree of variation in values across different evaluation schemes for the same indicator. A larger standard deviation signifies greater disparity in values among schemes, providing more information and thus warranting a higher weight. The conflict between evaluation indicators is reflected by their correlation coefficient. If two indicators exhibit strong positive correlation, it indicates weaker conflict between them, providing less information and thus a smaller weight. Therefore, based on the above perspectives, for an evaluation system with n indicators and m schemes to be evaluated, we can construct indicator information content based on these two characteristics.

Let C_j denote the information content contained in the j th evaluation indicator. Then, C_j can be expressed as:

$$C_j = \sigma_j \cdot \sum_{i=1}^{n} (1 - r_{ij}), \quad j = 1, 2, \cdots, n \tag{3}$$

In the formula: σ_j denotes the standard deviation of the j th evaluation indicator, calculated as follows:

$$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_{ij} - \mu_j)^2} \tag{4}$$

$$\mu_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij} \tag{5}$$

r_{tj} is the correlation coefficient between indicator t and indicator j , calculated as follows:

$$r_{ij} = \frac{\sum_{i=1}^{m} (x_{it} - \mu_t)(x_{ij} - \mu_t)}{\sqrt{\sum_{i=1}^{m} (x_{it} - \mu_t)^2} \sqrt{\sum_{i=1}^{m} (x_{ij} - \mu_j)^2}} \tag{6}$$

For the CRITIC method, the larger the value of C_j, the greater the information content contained in the j th indicator and the higher its relative importance. Therefore, the objective weight of the j th indicator is:

$$\beta_j = \frac{C_j}{\sum_{j=1}^{n} C_j}, \quad j = 1, 2, \cdots, n \tag{7}$$

The CRITIC method not only considers the impact of indicator variability on weighting but also accounts for conflicts among indicators. It represents a more objective weighting approach than entropy weighting and standard deviation weighting, yielding weights that better align with the objective reality of the data.

3) Least Squares Method for Determining Combination Weights[22]

To establish combination weights for different evaluation indicators of college students' employment capabilities in the AI era, an optimization model based on the least squares method was developed. This approach aims to verify the consistency between subjective and objective evaluations while enhancing weighting accuracy.

The subjective weights for each indicator are:

$$\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_n]^T \tag{8}$$

From equation (8), the objective weight of the indicator can be obtained as:

$$\beta=[\beta_1,\beta_2,\cdots,\beta_n]^T \tag{9}$$

The optimal combination of indicator weights to be obtained is:

$$\omega=[\omega_1,\omega_2,\cdots,\omega_n]^T \tag{10}$$

When evaluating a system comprising m schemes, each with n indicators, the data matrix is represented as $X=(x_{ij})_{m\times n}$. For all indicators of the evaluated object, the deviation between the indicator values under optimal weighting and those under the subjective-objective weighting method should be minimized. Therefore, establish a least-squares optimization combination evaluation model:

$$\begin{cases}\min F(\omega)=\sum_{i=1}^{m}\sum_{j=1}^{n}\{[(\alpha_j-\omega_j)x_{ij}]^2+[(\beta_j-\omega_j)x_{ij}]^2\}\\ \sum_{j=1}^{n}\omega_j=1,\omega_j\geq 0\end{cases} \tag{11}$$

The optimal solution is obtained using the Lagrange multiplier method, with the objective function defined as $L(\omega,\lambda)$:

$$L=\sum_{i=1}^{m}\sum_{j=1}^{n}\{[[\alpha_j-\omega_j)x_{ij}]^2+[[\beta_j-\omega_j)x_{ij}{}^2]\}+2\lambda(\sum_{j=1}^{n}\omega_j-1) \tag{12}$$

From the conditions for the existence of extrema, it follows that:

$$\frac{\partial L}{\partial\omega_j}=-\sum_{i=1}^{n}2(\alpha_j+\beta_j-2\omega_j)x_{ij}^2+2\lambda=0,\ j=1,2,\cdots,n \tag{13}$$

$$\frac{\partial L}{\partial\lambda}=2\left(\sum_{j=1}^{n}\omega_j-1\right)=0 \tag{14}$$

It can be simplified to:

$$\begin{bmatrix}B & e\\ e^T & 0\end{bmatrix}\begin{bmatrix}\omega\\ \lambda\end{bmatrix}=\begin{bmatrix}C\\ 1\end{bmatrix} \tag{15}$$

Among them:

$$B=diag\left[\sum_{i=1}^{m}x_{i1}^2,\sum_{i=1}^{m}x_{i2}^2,\cdots,\sum_{i=1}^{m}x_{im}^2\right] \tag{16}$$

$$e=[1,1,\cdots,1]^T \tag{17}$$

$$\omega=[\omega_1,\omega_2,\cdots,\omega_n] \tag{18}$$

$$C=\left[\sum_{i=1}^{m}\frac{1}{2}(\alpha_1+\beta_1)x_{i1}^2,\sum_{i=1}^{m}\frac{1}{2}(\alpha_2+\beta_2)x_{i2}^2,\cdots,\sum_{i=1}^{m}\frac{1}{2}(\alpha_n+\beta_n)x_{in}^2\right]^T \tag{19}$$

Solving equation (18) yields:

$$\omega=B^{-1}\left[C+\frac{1-e^TB^{-1}C}{e^TB^{-1}e}e\right] \tag{20}$$

2.3.5 College Student Employment Forecast Model

Student employability is a critical factor for educational institutions at all levels. In employability prediction models, an accurate feature selection process is essential to develop effective predictive models. An efficient deep learning model combining improved Random Forest (RF) and Deep Belief Network (DBN) is proposed for student employability prediction [23]. The proposed model operates in three stages: data preprocessing, optimal feature selection, and employability prediction. First, data consistency is achieved through data preprocessing. Subsequently, optimal feature selection is performed based on the improved RF algorithm. Finally, the DBN model is employed to predict student employment rates.

1) Data Preprocessing

Data preprocessing is a data mining strategy that transforms input data into a format suitable for further processing. First, credit scores are assigned to “text” data type attributes such as place of origin and major. Subsequently, z-score normalization is applied to eliminate noise within the dataset:

$$D'=\frac{D-(\bar{X})}{\delta(X)} \tag{21}$$

In Equation (1), D denotes the original dataset, D' represents the normalized data, $\bar{X}$ is the feature mean, and $\delta(x)$ is the feature standard deviation.

2) Feature Selection Based on an Improved RF Algorithm

An enhanced algorithm combining PCA and RF is employed to reduce feature dimensions while preserving original data information. The resulting features are then input into the DBN prediction model to improve computational efficiency and accuracy in feature extraction. The optimal feature subset is obtained through majority voting based on the classification results of individual decision trees.

PCA is widely applied for feature dimension reduction to decrease neural network computation time and enhance processing speed. Let the normalized feature set be $X^{'}=\{x_1^1,x_1^2,x_i^j,\ldots,x_m^n\}$ where j denotes decision variables.

A linear transformation yields the covariance matrix R:

$$R=\frac{1}{n}(X)^TX \tag{22}$$

Solve $|\lambda I-R|=0$ to obtain the eigenmatrix λ, then compute the cumulative contribution β_i:

$$\beta_i = \sum_{i=1}^{k} \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{23}$$

Thus, we obtain the top k principal component features of β_i between 75% and 95%, which encompass most of the original variable information.

After PCA dimensionality reduction, RF evaluates feature importance to select the optimal feature subset. The RF algorithm sets approximately one-third of the samples as the unselected portion, treating these samples as out-of-bag data. By perturbing the out-of-bag data not used in decision tree training, it calculates classification accuracy differences to determine feature importance.

The specific RF algorithm workflow is as follows:

(1) Perform bootstrap sampling using M feature subsets to generate M decision trees, each constructed independently;

(2) Set $m=1$ and train decision tree T_m. Use the mth dataset as training data and compute the accuracy L_m of the mth out-of-bag data point;

(3) Rearrange the features f within the out-of-bag dataset and compute the accuracy L_m^k;

(4) Repeat steps (2) and (3) for all sample datasets $m = 2, 3, \cdots, M$;

(5) Calculate the classification accuracy error after feature rearrangement, expressed as:

$$e_m^f = L_m - L_m^f \tag{24}$$

(6) Calculate the impact of features on the accuracy of out-of-bag data:

$$e^f = \frac{1}{M} \sum_{m=1}^{M} e_k^f \tag{25}$$

(7) Calculate the variance of e^f:

$$S^2 = \frac{1}{M-1} \sum_{m=1}^{M} (e_m^f - e^f)^2 \tag{26}$$

(8) Based on Equations (24) and (25), compute the importance of feature f: $f_F = e^f / S$

(9) Obtain the posterior f_F for all features. Generate feature subsets by sequentially removing one feature at a time from the sorted feature set. Calculate the accuracy of each feature subset, ultimately selecting the subset with the highest accuracy as the optimal feature subset.

3) Employment Prediction Model

The proposed method employs a deep learning model based on Deep Belief Networks (DBN) to predict student employment outcomes. Specifically, an enhanced Random Forest (RF) algorithm is trained independently to obtain a weight matrix, which is then used to train the DBN prediction model. The enhanced RF algorithm validates the effectiveness of extracted features by reconstructing the original data. Subsequently, the weight matrix derived from RF is integrated with the DBN model, ultimately trained on input data for the employment prediction task.

Within the DBN, Restricted Boltzmann Machines (RBMs) serve as the hidden layer for each subnetwork and the visible layer for the subsequent layer. Each layer in the DBN undergoes an efficient layer-wise process determining how its variables depend on those of the preceding layer. The proposed DBN network comprises multiple RBMs with visible and hidden layers, culminating in a final layer employing logistic regression for classification. First, different feature spaces of the vector are mapped, and each layer of the RBM network is trained unsupervised to preserve all feature information. Subsequently, model fine-tuning is performed. Finally, the output feature vector from the RBM serves as the input feature vector for the next RBM.

In the RBM model, let the visible layer be represented as v_i and each hidden layer as h_i. The weights between v_i and h_j are guided by w_{ij}. The vectors c and b represent the biases between visible and hidden nodes. The values of b_i, c_i and w_{ij} across all RBMs in the model constitute the θ parameters in the DBN. The parameter θ appears as the joint state of the hidden layers and the probability form of the energy function.

Every pair of adjacent hidden layers in the DBN forms an RBM, where the input layer of the current RBM is the output layer of the preceding RBM. The joint probability distribution of the visible vector v and the l hidden layers $h_k, k=1,2,\cdots,l,h_0=u$ can be expressed as:

$$\begin{aligned} P(h_1,h_2\cdots,h_l \mid v) &= P(h_l \mid h_{l-1})_P(h_{l-1} \mid h_{l-1})\cdots P(h_1 \mid v) \\ &= \prod_{k=1}^{l} P(h_k \mid h_{k-1}) \end{aligned} \tag{27}$$

The bottom-up inference probability from the visible layer v to the hidden layer h_k is defined as:

$$p(h_k \mid h_{k-1}) = \sigma(b_j^k + \sum_{j=1}^{m} w_{ij}^k h_j^{k-1}) \tag{28}$$

In equation (28), b^k denotes the bias of the kth layer. Similarly, the top-down inference probability is defined as:

$$p(h_{k-1} \mid h_k) = \sigma(b_j^{k-1} + \sum_{j=1}^{m} w_{ij}^{k-1} h_j^k) \tag{29}$$

DBN training consists of two steps: pre-training and fine-tuning using the backpropagation (BP) algorithm. A final layer is added to the DBN architecture, representing the desired output or target, followed by supervised learning of the DBN model via the BP algorithm during fine-tuning. The BP algorithm refines the features learned in the hidden layers of the previously trained RBMs. This process leverages trained weights to overcome local minima.

Pre-training is implemented through a layer-by-layer training method known as the “greedy layer” training algorithm. This phase learns the parameters of each layer within the RBMs. The first RBM is trained first to reconstruct its input as accurately as possible. The hidden layer of the first RBM is then treated as the visible layer for the second RBM, whose output is fed into the visible layer of the next RBM, and so on. This process repeats until every predefined hidden layer in the network is trained. This pretraining step acquires initial parameters before supervised training.

The fine-tuning process is the supervised learning phase that involves using labeled data to train the DBN model using the top-down approach. The phase makes use of the optimum weights and biases derived from each step of the pre-training stage for RBM. The fine-tuning process makes use of parameters learned from training in order to prevent problems related to getting stuck at local minima and over-fitting due to random initialization of networks. The training ends once a certain number of iterations or error rate is achieved.

3 Research on Evaluating College Students' Employment Competency Based on the USEM Model

This chapter will establish an evaluation framework for college students' employment capabilities based on the USEM model, focusing on four dimensions: subject comprehension (U), comprehensive skills (S), personal aptitude (E), and metacognition (M). Utilizing the proposed evaluation model for university students' employment capabilities, this framework enables a comprehensive assessment of their employability.

3.1 Construction of the Employment Competency Evaluation Indicator System

The USEM model intuitively reflects the complex relationship among job seekers' comprehensive qualities, problem-solving abilities, disciplinary transfer capabilities, individual self-assessment, and employment competencies. It provides a reference for constructing an evaluation index system for college students' employment capabilities and holds significant importance for in-depth exploration of pathways to enhance their employability.

Considering the complex and diverse factors influencing university students' employment capabilities in the context of the pandemic and multiple overlapping factors in the new era, as well as the differences in evaluation indicator systems across regions, universities, and majors, this paper constructs an evaluation indicator system for university students' employment capabilities based on literature review and by integrating relevant scholarly research. The specific evaluation indicator system is shown in Table 1. As shown, this study approaches the evaluation framework from four dimensions: disciplinary understanding (U), comprehensive skills (S), individual endowment (E), and metacognition (M), while also incorporating environmental adaptability into the employment competency assessment system for university students.

Table 1: Evaluation index system of students ' employability

Target layer	Criterion layer	Index layer
Employability of college students	Subject understanding (U)	Learning attitude (U1)
		Subject professional knowledge (U2)
		Competition research experience (U3)
		Related professional certificate (U4)
		Foreign Language Proficiency (U5)
	Comprehensive skills (S)	Information processing ability (S1)
		Communication skills (S2)
		Environmental adaptability (S3)
		Self-management ability (S4)
		Teamwork Capability (S5)
	Individual endowment (E)	Honesty (E1)
		Analytical Ability (E2)
		Hardworking (E3)
		Self-cognition (E4)
		Responsibility (E5)
	Metacognition (M)	Innovation ability (M1)
		Career planning ability (M2)
		Personal Image Management (M3)
		Language Organization Ability (M4)
		Work experience (M5)

3.2 Determination of Weighting for Employment Competency Evaluation Indicators

Following the procedures of the improved G1 method and CRITIC method, experts from university employment departments were invited to score and rank the 20 indicators selected for this study. The scoring criteria are shown in Table 2.

Table 2: Expert scoring criteria

Importance	Score
Especially important	9~10
More important	6~8
Generally important	3~5
Not important	1~2

Based on the scoring data provided by four experts for the employment competency evaluation indicators of college students in the new era, this paper proposes a university student employment competency evaluation model to derive both subjective and objective weights for the indicators. Finally, a combined weighting value integrating subjective and objective weights is obtained using the least squares method, with the results shown in Figure 2. From the criterion perspective, the combined weights for each indicator correspond to varying degrees of subject comprehension, comprehensive skills, individual endowment, and metacognitive weight. Among these, individual endowment accounts for 26.02% of the weight, indicating that a strong sense of self-awareness and efficacy, externalized as communication skills and analytical problem-solving abilities, is the most critical factor for college students to enhance their employability. Additionally, the combined weight of comprehensive skills and subject comprehension accounts for 55.2% of the total. This demonstrates the importance of the academic success experienced at university level, whereby having professional theory and practical ability are both essential elements in developing job preparedness. The metacognitive aspect of job preparedness is the least important out of the four, comprising 18.78% of total weightage.

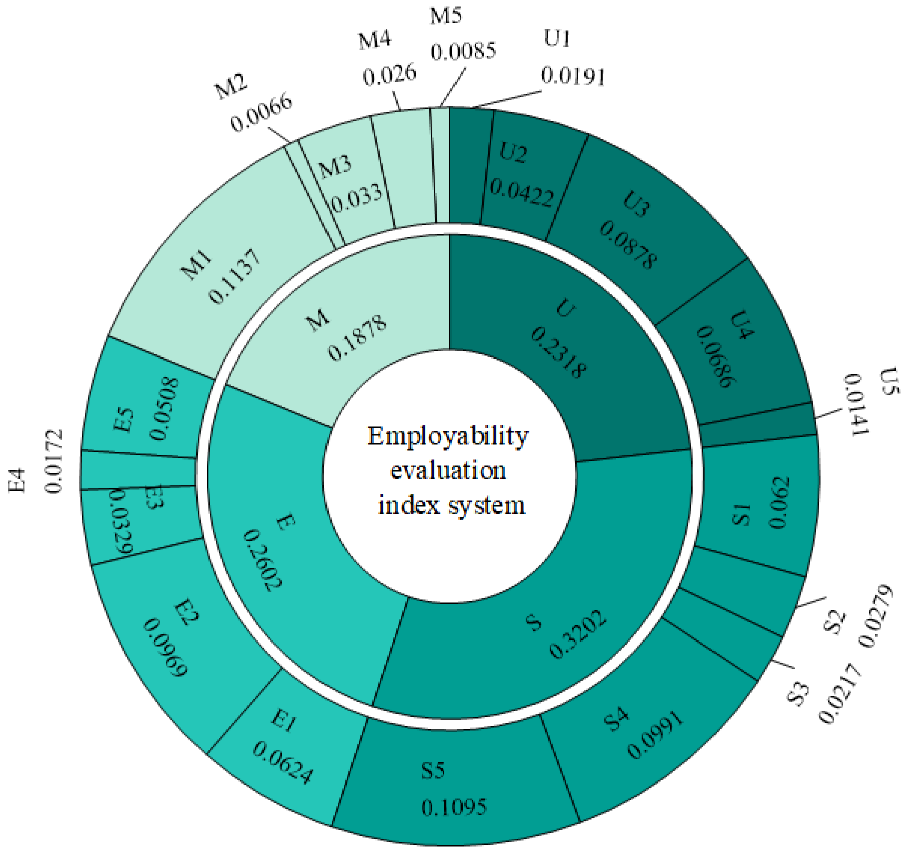

Figure 2: Employability evaluation index system

Comparison between the results obtained using G1, CRITIC, and least square methods is shown in Figure 3. The comparison suggests that the gap between the knowledge of employers and college students regarding job-related competencies is due to the difference in opinion regarding individual endowments. College students tend to focus more on individual endowments like self-qualities and self-efficacy because they believe that qualities such as integrity, analytical ability, and hard work can impress employers more easily.

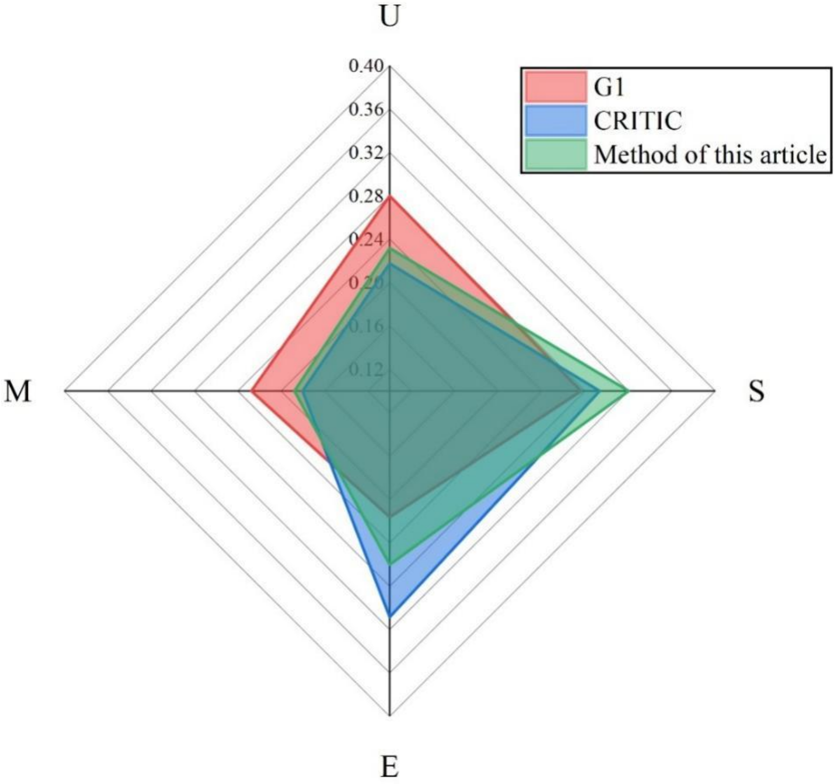

Figure 3: Weight comparison of criterion layer

3.3 Analysis of Student Employment Competency Evaluation Results

Statistical analysis of the study results was done using Stata software. Indicators associated with subject knowledge, comprehensive skills, individual aptitude, and metacognitive ability were considered. Scoring results for different criterion levels are detailed in Figure 4. Based on average values, indicators can be broadly classified into three categories: low-scoring, mid-range, and high-scoring. The overall employment competency score for students was 5.08, indicating an average level of employment readiness among surveyed students. The scores for the four dimensions—subject comprehension, comprehensive skills, individual aptitude, and metacognition—were 1.034, 1.781, 1.242, and 1.023, respectively. The overall proficiency levels, ranked from highest to lowest, are: Comprehensive Skills > Individual Endowment > Academic Understanding > Metacognition. Comprehensive Skills achieved the highest score, indicating that the surveyed students possess strong abilities in information processing, communication and expression, environmental adaptation, self-management, and teamwork.

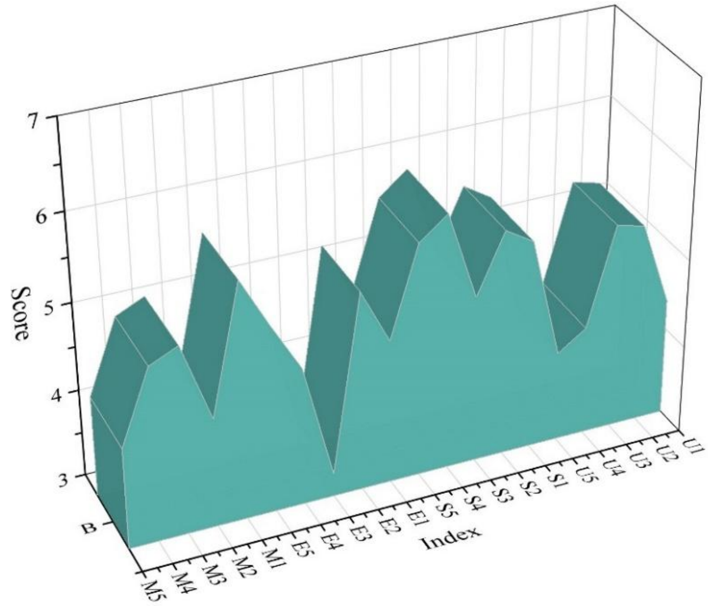

Figure 4: Score of indicators

Comparing the results of G1 level, CRITIC level, and the least squares combination level, the specific comparison results are shown in Figure 5. From the perspective of individual indicators, the indicators with the highest overall levels are innovation ability under metacognition, self-management ability and teamwork ability under comprehensive skills, indicating the importance of innovation ability, teamwork, and self-management in enhancing college students' employability. The indicators with the lowest overall levels were career planning ability and work experience under metacognition. The five indicators under the metacognitive criteria layer exhibited both the highest and lowest levels, indicating that college students' metacognitive abilities vary significantly in the context of the AI era. There is an urgent need to strengthen students' self-awareness and self-understanding capabilities.

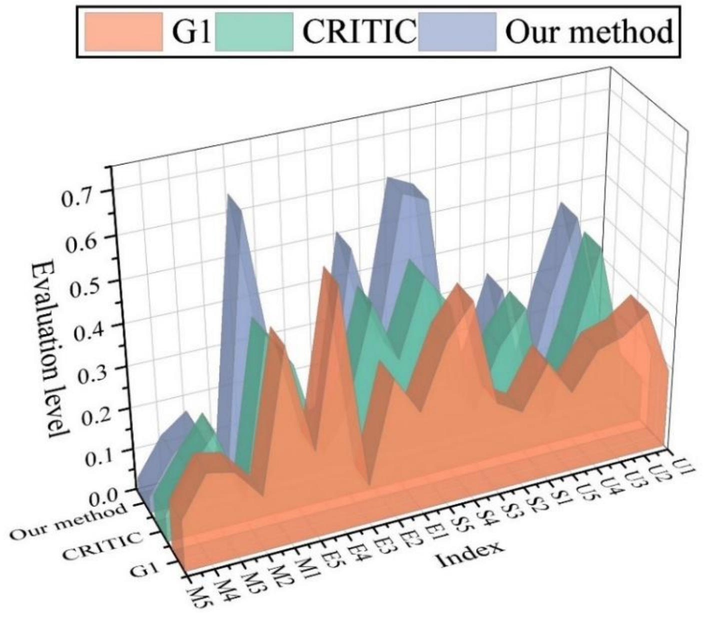

Figure 5: Comprehensive evaluation level

4 Research on Deep Learning-Based Employment Prediction for College Students

This section will utilize the student employment prediction model proposed in this paper—based on an improved random forest and deep learning approach—to forecast employment outcomes for university students, drawing upon relevant research data from surveyed students at University A.

4.1 Preprocessing of Employment Forecast Data

Student graduation destinations are categorized into four types: employment, further education, studying abroad, and awaiting employment. Since further education and studying abroad can be understood as domestic and international advanced studies respectively, both extend the duration of education and are equivalent to delayed employment. Therefore, this paper excludes these two graduation destinations from discussion.

According to the undergraduate training program established by University A, the classification of student training courses is shown in Table 3. As seen in the table, student training courses can be divided into nine modules: major core courses, disciplinary foundation courses, disciplinary education courses, foundational courses, public required courses, skill courses, educational practice courses, professional practice courses, and quality development practice courses.

Table 3: Modules of training courses for students

Training courses	Module	Code
Students ' training courses	Professional core courses	C1
	Basic Subject Courses	C2
	Subject education courses	C3
	Basic courses	C4
	Public compulsory courses	C5
	Skills courses	C6
	Educational Practice Course	C7
	Professional practice courses	C8
	Quality practice	C9

4.2 Analysis of Employment Forecast Performance

To design an effective and robust DBN-based prediction model, hyperparameter optimization and weight optimization are performed during training. Key parameters include the number of hidden layers, the number of neurons in each hidden layer, batch size, number of training iterations, learning rate, and others.

To validate the employment prediction results of the proposed model, this study additionally selected employment data from 300 graduates of the Class of 2024 as the experimental dataset. This dataset was divided into training and testing sets at a ratio of 9:1. Accuracy evaluation of the prediction model was conducted according to the outcome of 100 experiments. The comparison of accuracy among the algorithm suggested in this paper and other benchmark algorithms, such as decision tree and SVM, is shown in Figure 6. As can be seen from the figure, the predicted data results of the algorithm in this paper have a relatively high degree of accuracy, reaching an average accuracy of 87.8%, which is higher than those obtained by other prediction algorithms. It is clear that the employment prediction model in this paper can predict the employment result of students more accurately. This will help provide data support to formulate policies that could help students find jobs.

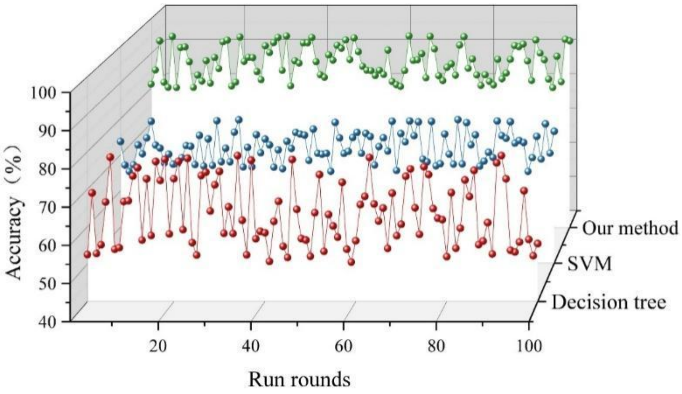

Figure 6: Comparison of prediction accuracy

4.3 Assessment of the Importance of Training Course Modules

In this part, the proposed employment prediction model is applied to estimate the significance of each module in the curriculum of student development at University A for employment prediction based on feature importance evaluation. The influence of various modules in the curriculum of student development on employment prediction is explored in detail. In the figure, P1 to P8 correspond to: Quality Practice, Professional Core Courses, Foundational Courses, Skill Courses, Discipline Foundation Courses, Discipline Education Courses, Professional Practice Courses, and Public Required Courses. The modules are ranked in descending order of importance: Quality Development Practice (0.22), Major Core Courses (0.191), Foundational Courses (0.18), Skill Courses (0.161), Discipline Foundation Courses (0.15), Discipline Education Courses (0.081), Major Practice Courses (0.06), and Public Required Courses (0.05). The results indicate that the modules of quality practice, professional core courses, foundational courses, skill courses, and disciplinary foundation courses are relatively important. In particular, quality practice capabilities play a primary role in graduate employment and are a key factor influencing university students' employment outcomes.

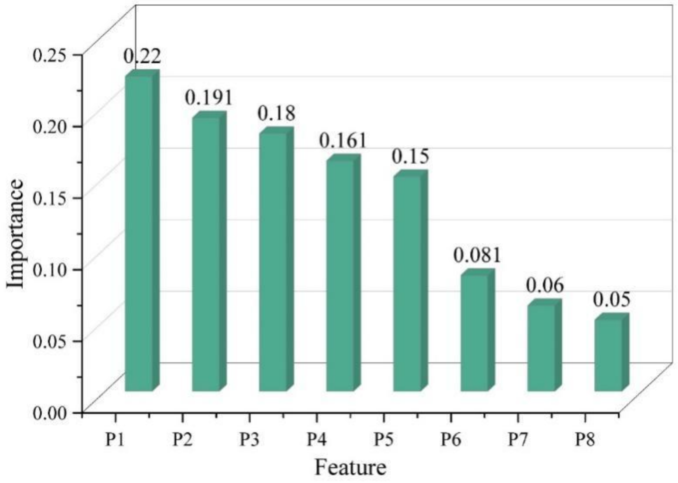

Figure 7: Feature importance ranking

5 Pathways for Cultivating College Students' Employment Competencies

Applying the student employment capability assessment model proposed in this paper to evaluate the employment capabilities of surveyed students at University A reveals significant disparities in their metacognitive abilities. There is an urgent need to enhance their self-awareness and self-understanding capabilities, with their overall employment capabilities barely reaching an average level. Integrating the findings from employment prediction research on the importance of various modules within student training curricula, this chapter will propose targeted pathways and strategies for cultivating university students' employment capabilities, thereby supporting graduate employment outcomes.

1) Rationally design student training curricula to enhance teaching quality.

Universities must closely align professional course offerings with economic development needs and adjust them based on market-driven career demands to strengthen graduates' competitiveness. Concurrently, institutions should prioritize improving teaching quality to elevate students' professional knowledge and skills. Courses should be scheduled rationally according to the importance of each training module.

2) Strengthen career planning education to foster sound employment perspectives.

Begin career planning education upon enrollment to help students clarify career goals, understand market demands, and improve self-awareness and professional competence. Universities should also guide students toward a positive employment mindset, emphasizing that securing a job is a process of realizing personal value and contributing to society.

3) Enhance cooperation between universities and industries to create more practical chances.

Universities need to increase cooperation with industries to provide additional internship opportunities to their students. By means of internships, students become more familiar with industrial developments and market requirements, thereby becoming more competitive in the labor market. At the same time, such cooperation will help universities to get more information about market demands and industry characteristics for educational and research purposes.

6 Conclusion

The evaluation index system of employment competency is built using the USEM framework, and then least square approach is applied in order to synthesize and weigh subjective and objective indicators. In terms of criterion dimension, the proportion of individual endowment takes up 26.02%, and the comprehensive skills along with disciplinary understanding account for 55.2% of the total weight. Metacognition weighting is relatively low, just occupying 18.78%. Calculated through statistics, the employment competency grade of surveyed students amounts to 5.08. According to the descending order of comprehensive proficiency, the dimension ranking results are: Comprehensive Skills (1.781)>Individual Endowment (1.242)> Disciplinary Understanding (1.034)>Metacognition (1.023). The ability of surveyed students to use comprehensive skills, including information processing and communication abilities, is strong. On performance test of hybrid student employment prediction model, the prediction precision reaches the average value of 87.8%, which outperforms other prediction algorithms. In addition, the feature importance is analyzed by the impact that different curriculum modules make on employment prediction results. From the top to the bottom, the importance of curriculum module is as follows: Quality Practice (0.22)>Professional Core Courses (0.191)>Foundational Courses (0.18)>Skill Courses (0.161)>Discipline Foundation Courses (0.15)>Discipline Education Courses (0.081)>Professional Practice Courses (0.06)>Public

Required Courses (0.05). Character development practice becomes the most important influence factor for employment of university students among all curriculum modules. Finally, according to the combination of employment capability assessment and employment forecast, some methods of cultivating university students' employability are put forward.

About the Author

Wen Zou was born in Xinxiang, Henan, China in 1989. She earned a Master's degree in Education from China West Normal University and currently works at Zhengzhou Technology and Business University. Her main research focuses on career education, occupational planning, and employment guidance.

References

[1] Felten, E. W., Raj, M., & Seamans, R. (2019). The occupational impact of artificial intelligence: Labor, skills, and polarization. NYU Stern School of Business.

[2] Långstedt, J., Spohr, J., & Hellström, M. (2023). Are our values becoming more fit for artificial intelligence society? A longitudinal study of occupational values and occupational susceptibility to technological substitution. Technology in Society, 72, 102205.

[3] Wu, Y. (2025). Analysis of the Current Situation of Artificial Intelligence Industry Development and the Demand for Applied Talents in Jilin Province. Frontiers in Educational Research, 8(7).

[4] Waltersmann, L., Kiemel, S., Stuhlsatz, J., Sauer, A., & Miehe, R. (2021). Artificial intelligence applications for increasing resource efficiency in manufacturing companies—a comprehensive review. Sustainability, 13(12), 6689.

[5] Hagemann, S., Sünnetcioglu, A., & Stark, R. (2019). Hybrid artificial intelligence system for the design of highly-automated production systems. Procedia Manufacturing, 28, 160-166.

[6] Pérez, J. B., & Falótico, A. J. A. (2019). Various perspectives of labor and human resources challenges and changes due to automation and artificial intelligence. Academicus, (20), 106.

[7] Liu, W. (2021, March). Research on the Requirements of Artificial Intelligence on Applied Talents Cultivation. In IOP Conference Series: Earth and Environmental Science (Vol. 687, No. 1, p. 012182). IOP Publishing.

[8] Türker, P. M., & Öztürk, M. (2025). Generative Artificial Intelligence and the 4C Learning Skills for the 21st Century. In Next-Generation AI Methodologies in Education (pp. 285-320). IGI Global Scientific Publishing.

[9] Gao, S. (2020, February). Innovative teaching of integration of artificial intelligence and university mathematics in big data environment. In IOP Conference Series: Materials Science and Engineering (Vol. 750, No. 1, p. 012137). IOP Publishing.

[10] Qian, L., Cao, W., & Chen, L. (2025). Influence of artificial intelligence on higher education reform and talent cultivation in the digital intelligence era. Scientific Reports, 15(1), 6047.

[11] Wu, Z., Liu, H. Y., & Deng, X. Y. (2024). Teaching Practices for the Cultivation of “AI+ X” Composite Talents in Higher Education: Challenges and Strategies. Education Science and Management, 2(3), 156-175.

[12] Wu, L. (2021, March). Construction of STEM Interdisciplinary Integration Model Supported by Educational Artificial Intelligence. In 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 769-772). IEEE.

[13] Cerna, L., & Chou, M. H. (2019). Defining “talent”: Insights from management and migration literatures for policy design. Policy Studies Journal, 47(3), 819-848.

[14] Papier, J. (2017). Improving college-to-work transitions through enhanced training for employment. Research in Post-Compulsory Education, 22(1), 38-48.

[15] Halper, L. R., Craft, C. A., & Shi, Y. (2020). Expanding the student employment literature: Investigating the practice of reflection in on-campus student employment. Journal of College Student Development, 61(4), 516-521.

[16] Ma, Y., & Li, X. (2018, December). Exploration on the Operating Mechanism of" Four Wheel Driving" Mode for Cultivating Students Innovative and Entrepreneurial Ability in Applied Undergraduate Colleges. In 2018 8th International Conference on Management, Education and Information (MEICI 2018) (pp. 645-650). Atlantis Press.

[17] Li, J., & Wang, X. (2022). An optimization model of applied career planning for innovative and entrepreneurial talents based on credible neural networks. Security and Communication Networks, 2022(1), 3580803.

[18] Chen, K., Tham, J., & Khatibi, A. (2025). Research on Strategies for Enhancing the Employment Ability of Vocational College Graduates from the Perspective of School Enterprise Cooperation. Frontiers in Educational Research, 8(4).

[19] Liu, Y., Wang, C., & Chen, Z. (2024). Exploration on the Paths to High-Quality Employment in Colleges and Universities under the Background of New-Quality Productive Forces. Journal of Modern Education and Culture, 1(3).

[20] Chao, C., Zhe, Z., & Yafang, L. (2021). Research on innovation and entrepreneurship education reform and university talent cultivation model innovation. Frontiers in Educational Research, 4(7).

[21] Krishnan Anath Rau. (2025). Research trends in criteria importance through intercriteria correlation (CRITIC) method: a visual analysis of bibliographic data using the Tableau software. Information Discovery and Delivery,53(2),233-247.

[22] A. A. Mizyukanova & G. P. Chikildin. (2025). Determination of the Dependence of the Frequency Properties on the Parameters of the Function Used in the Least Squares Method of Parametric Identification. Optoelectronics, Instrumentation and Data

Processing,61(2),220-225.

[23] Piotr Gajewski,Boris Čule & Nevena Rankovic. (2023). Unveiling the Power of ARIMA, Support Vector and Random Forest Regressors for the Future of the Dutch Employment Market. Journal of Theoretical and Applied Electronic Commerce Research,18(3),1365-1365.