



The construction of deep learning employment demand prediction and accurate recommendation system for the full cycle of "recruit training and Create"

Yanbin Sun^{1,*}

¹ Innovation and Entrepreneurship College, Pingdingshan University, Pingdingshan, 467000, Henan, China

SUMMARY: *In order to solve the problems of demand perception lag, training feedback dispersion and recommendation service fragmentation in the "recruit and create" chain of colleges and universities, this paper constructs a full-cycle deep learning employment demand prediction and accurate recommendation system. Based on 84216 job records and student training, internship employment and innovation and entrepreneurship data, this paper establishes a heterogeneous correlation model of job demand, user ability and training resources, and integrates Transformer semantic coding, temporal feature learning and graph relationship modeling to realize the joint prediction of job demand intensity, ability gap and resource compensation path. The system further designs a personalized recommendation and interactive feedback mechanism to form a closed-loop service process of "prediction- matching-intervention-update". The experimental results show that the Accuracy of the proposed model is 89.3%, the Macro-F1 is 88.1%, and the Top-3 hit rate is 95.6%. In the real application test, the proportion of effective subsequent behaviors triggered after recommendation reaches 72.8%, and the decision time of students' first effective delivery is reduced from 26.4 minutes to 18.7 minutes. The research provides a deployable computing scheme for the digitalization, collaboration and intelligence of university employment service.*

KEYWORDS: *Employment demand forecasting; Precise recommendation; Deep learning; Recruit training to create a full cycle*

1 Introduction

With the accelerated evolution of the digital economy, information generation, ability evaluation and job mobility in the job market are continuously being reshaped by platform data and intelligent algorithms. For colleges and universities, talent training is no longer a single point of output before graduation, but a continuous system engineering throughout enrollment portrait, process training, employment matching and innovation and entrepreneurship transformation. Especially under the background of the continuous promotion of the integration reform of "recruiting and training to create", the job demand of employers is updated frequently, and the skill structure shows obvious dynamic, complex and timing differences. The traditional employment analysis method relying on manual statistics, experience judgment and static questionnaire has been difficult to support the forward-looking identification of job trends. It is also difficult to provide students with targeted growth suggestions and job recommendations.

Existing research mainly focuses on recruitment text parsing, person-job matching

*4904@pdsu.edu.cn

<https://doi.org/10.65102/is2026226>

calculation, and resume semantic modeling. Deep learning methods have shown strong capabilities in skill extraction, job representation and matching prediction. However, from the perspective of application chain, related work still mainly focuses on the local optimization of the recruitment end or the job search end, and the correlation between the full-cycle data of "enrollment, training, employment and entrepreneurship" is underutilized. On the one hand, the enrollment characteristics, course attendance, competition experience, internship records and employment directions within colleges and universities are often scattered in different business systems, with heterogeneous data structures and different semantics, which makes it difficult for the model to form stable cross-stage cognition. On the other hand, many recommendation methods pay more attention to the current post matching score, and do not consider the phased changes of post requirements, the ability growth path and the intervention effect of training resources, so it is difficult to truly serve collaborative education and dynamic decision-making.

Based on this, this paper puts the employment demand prediction and accurate recommendation in the full-cycle scenario of "recruiting and training for creation", and tries to build an intelligent system that takes into account prediction, matching, feedback and service implementation. Starting from multi-source heterogeneous data modeling, this paper integrated post texts, students' ability portraits, training process data and innovation and entrepreneurship behavior data, and established a deep learning employment demand prediction model for the full cycle. On this basis, the association recommendation mechanism between job requirements, user capabilities and training resources is further constructed, so that the system can not only judge what the market needs, but also answer what students are currently suitable for, what is missing, and how to make up for it. This paper hopes to provide a computable, deployable and continuous optimization path for the digital transformation of "recruit, train and create" collaborative service in colleges and universities.

2 Related Research

In recent years, the research on employment intelligent service has obviously shown a trend of transformation from experience-driven to data-driven. Focusing on online recruitment, job ability identification and person-position matching, researchers have gradually shifted from rule-based keyword search in the early stage to deep representation learning and recommendation modeling. Mashayekhi et al. [1] systematically sorted out the task boundaries and technical challenges of the electronic recruitment recommendation system, and pointed out that the sparsity of job semantics, feedback delay and evaluation bias were important factors restricting the system performance. Kumar et al. [2] discussed the fairness problem in recruitment recommendation from both technical and legal perspectives, indicating that the algorithm should not only pursue matching accuracy, but also take into account interpretability and bias control. Focusing on the modeling of person-position adaptation, Yao et al. [3] improved the job understanding ability through knowledge enhancement, Wang et al. [4] used the co-attention mechanism to depict the association between candidate portraits and recruitment history, and Huang et al. [5] further explored the implicit relationship of resumes to improve the adaptability of recommendation results to complex occupational backgrounds. Kokkodis and Ipeirotis [6], Brek and Boufaïda [7], Chen et al. [8], Cao et al. [9], and Guan et al. [10] have shown that the recruitment recommendation model is changing from shallow matching to multi-source collaborative representation from semantic structure, relational network to hierarchical pre-training.

At the same time, job demand forecasting research has also transferred from "job name statistics" to the calculation stage of "skill structure identification and trend inference".

Akkasi[11] used an interpretable Transformer integration model to parse technical and non-technical skills in job descriptions, and Tzimas et al. [12] converted online recruitment texts into labor market intelligence, providing a structured path for demand monitoring. Weichselbraun et al. [13] further applied deep learning to the evaluation of future skills readiness, indicating that job demand not only has the current matching attribute, but also has obvious forward-looking prediction value. Senger et al. [14] and Gnehm et al. [15] conducted a review and empirical study on skill extraction and fine-grained classification in recruitment texts, indicating that the key to job demand representation is not only to extract "what skills", but also to identify "how skills are combined and changed".

In parallel with the research on the recruitment end, the research on the prediction of students' employability and training intervention is developed. Haque et al. [16] and Luo et al. [17] applied machine learning and deep learning to graduate employment prediction, and proved that learning behavior, academic performance and practical experience had strong explanatory power on employment results. Frej et al. [18] proposed that the course recommendation system must consider the changes in the labor market, indicating that it is difficult to form an effective closed loop if the allocation of training resources is separated from the job demand. Yamashita et al. [19] and Decorte et al. [20] expanded the research basis of career development prediction from the perspectives of anonymous resume dataset construction, career trajectory modeling and skill matching, respectively. Ong and Lim[21] verified the feasibility of data-driven career insight from the perspective of skill recommendation. The relevant results provide methodological support for the intelligent employment service in colleges and universities, but they also expose a common deficiency: many studies only cover a single link in recruitment, job hunting, course recommendation or career path, and have not put enrollment characteristics, training process, employment destination and innovation and entrepreneurship activities into a unified computing framework for linkage modeling.

As shown in Table 1, existing research has formed a solid foundation in job text understanding, person-job matching and skill recommendation, but there are still three types of vacancies for the full-cycle scenario of "recruiting and training for creation". First, there is a lack of unified representation between multi-source heterogeneous data, and it is difficult to aligned enrollment portraits, course processes, training records and job requirements in the same semantic space. Secondly, the model output mostly stays at the matching score, lacking the mechanism to return the prediction results to the training resource allocation and ability compensation. Third, system research rarely discusses the deployment collaboration among prediction module, recommendation module and interactive service module. Based on this, this paper tries to put employment demand prediction and accurate recommendation into the overall design of the full-cycle business chain, and realizes the integrated linkage of demand identification, ability characterization, resource recommendation and service feedback on the basis of deep learning modeling.

Table 1: Review of related research and the entry point of this paper

Research Direction	Representative References	Main Content	Existing Limitations	Implications for This Study
E-recruitment recommendation and fairness analysis	[1][2]	Reviews recruitment recommendation tasks and discusses system challenges, fairness, and compliance issues	Focuses more on recruitment platform scenarios and provides insufficient coverage of full-cycle services in higher education	The prediction and recommendation system should balance accuracy, fairness, and interpretability
Deep modeling for person-job matching	[3][4][5][6][7][8][9][10]	Improves matching performance through knowledge enhancement, attention mechanisms, relation networks, and pretrained models	Mainly concentrates on static matching between job seekers and positions, with limited consideration of the training and cultivation process	A unified cross-stage representation should be constructed to connect job demand with student growth trajectories
Job text parsing and demand identification	[11][12][13][14][15]	Extracts skills from recruitment texts, generates labor market insights, and predicts future demand	Largely focuses on skill extraction itself, with insufficient consideration of demand dynamics and resource linkage	Demand identification results should be transformed into course and training recommendations
Employment prediction, course recommendation, and skill recommendation	[16][17][18][19][20][21]	Predicts employment outcomes and provides recommendations based on learning data, resume data, and market information	The tasks remain relatively fragmented and have not yet formed a closed loop of "admission-training-employment-innovation and entrepreneurship"	Employment prediction, resource recommendation, and interactive feedback should be integrated into a unified system

3 Construction and optimization of employment demand forecasting model for the full cycle of "recruiting and training for Creation"

3.1 Full-cycle multi-source heterogeneous data modeling and fusion prediction model design

The employment demand prediction under the scenario of "recruiting and training to create" is not a simple extrapolation of the number of jobs, but to identify the continuous evolution relationship between enrollment entrance, training process, employment destination and innovation and entrepreneurship activities. The task also includes text semantic understanding, behavior sequence modeling, relationship dependence propagation and time series trend perception. If a single statistical regression or static classification model is still used, it can only capture local correlation, and it is difficult to simultaneously depict the dynamic changes of job ability requirements, the stage differences of students' ability growth, and the delayed impact of on-campus resource supply on the final employment results. Based on this, this paper

constructs a fusion prediction model for full-cycle multi-source heterogeneous data, maps the information of job demand side, student growth side and training resource side into a unified representation space, and completes the joint prediction of future job demand intensity and ability gap on this basis. The overall process is shown in Figure 1.

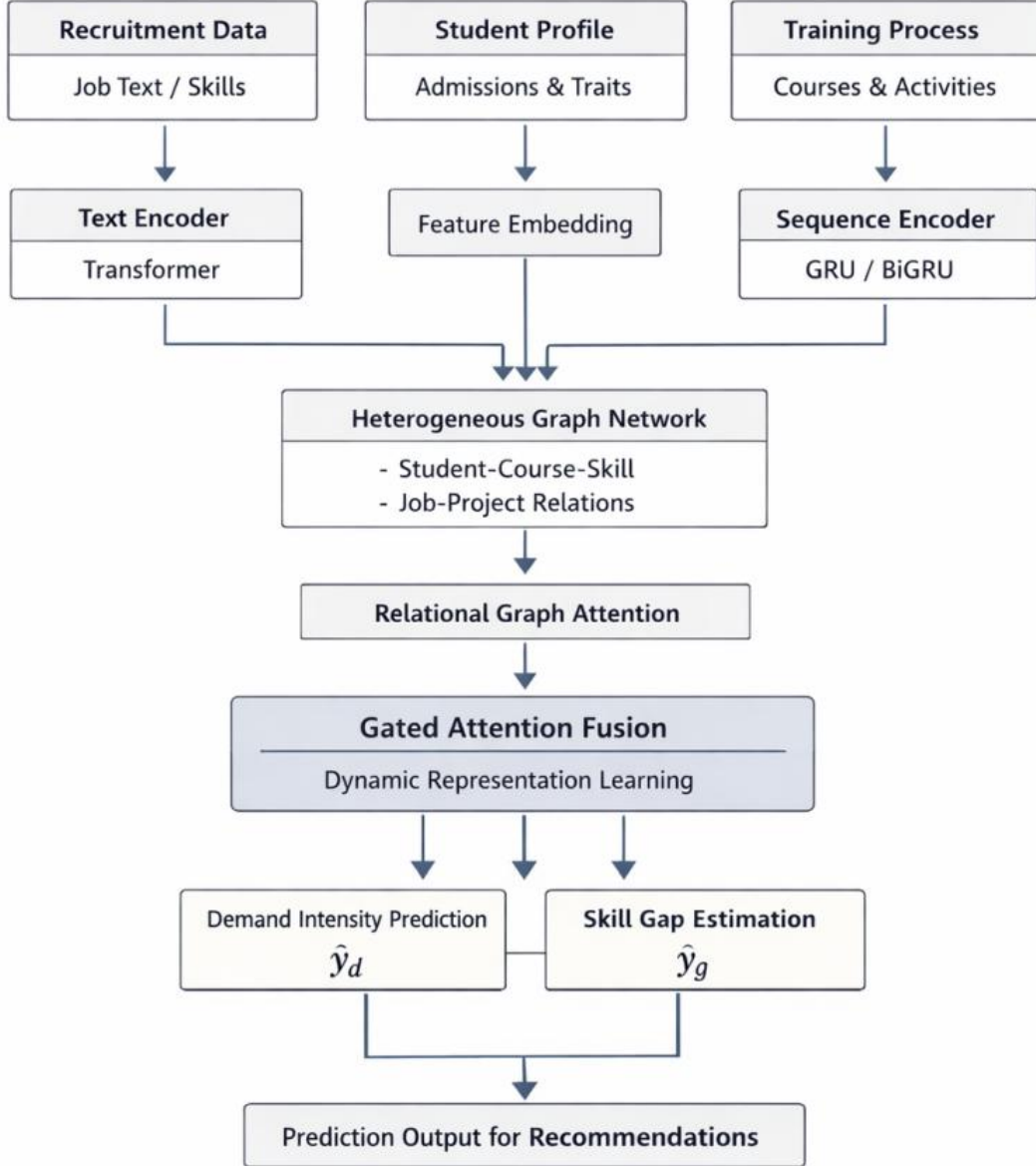


Figure 1: Structure diagram of full-cycle multi-source heterogeneous data fusion prediction model

In the input layer, the system uses the time window t as the basic modeling unit to construct the full period observation sample:

$$X_t = \{J_t, S_t, C_t, E_t, I_t\} \quad (1)$$

Among them, J_t represents demand data such as recruitment post text, skill label and industry category; S_t represents enrollment portraits, basic ability and interest characteristics; C_t represents training process data such as course attendance, score fluctuation, competition practice and certificate acquisition; E_t represents employment flow, signing results, job

feedback and other results data. I_t refers to entrepreneurial training, project participation, incubation record, and market environment indicators. Considering that the above data structure contains discrete categories, continuous values, text sequences and graphical relationships, we first perform missing completion, time alignment, category coding and standardization, and then send them into different coding channels respectively.

The job requirement channel uses the domain-specific Transformer encoder to semantically model the job description, skill requirements and responsibility expression to obtain the job requirement vector h_t^J . The training process channel uses gated recurrent unit to encode the course-practice-evaluation sequence of students in multiple semesters, and obtains the growth state vector h_t^C . On the other hand, the association relationship channel organizes "students-course-skills-position-entrepreneurial project" into a heterogeneous graph, and extracts cross-entity dependencies through graph attention network to form a relationship representation h_t^G . The three types of representations are not simply concatenated, but dynamically fused by gated attention mechanism:

$$\alpha_i = \frac{\exp(w^\top h_t^i)}{\sum_k \exp(w^\top h_t^k)}, \quad i \in \{J, C, G\} \quad (2)$$

$$z_t = \sum_i \alpha_i h_t^i \quad (3)$$

where, α_i is the contribution weight of each channel under the current time window and z_t is the full-cycle representation after fusion. The design can avoid the distortion of fixed weights under different majors, different employment seasons and different job clusters, so that the model pays more attention to the job semantics in the stage of high demand fluctuation, emphasizes the growth trajectory in the stage of cultivation and differentiation, and strengthens the graph structure relationship in the cross-link linkage analysis.

In the output layer, this paper does not limit the prediction target to a single job hit probability, but adopts a dual-task joint learning method to simultaneously output the post demand intensity prediction value y_t^d and the capacity gap prediction value \hat{y}_t^g :

$$\hat{y}_t = \text{MLP}(z_t), \mathcal{L} = \lambda_1 \mathcal{L}_d + \lambda_2 \mathcal{L}_g \quad (4)$$

Among them, \mathcal{L}_d is used to constrain the post demand trend prediction error, and \mathcal{L}_g is used to measure the deviation between the current ability of students and the target post requirements. This output method enables the prediction results to directly serve the subsequent recommendation process, not only answering the question "which positions are in increasing demand", but also answering "which capabilities have not yet been supplemented and which training resources should be involved".

From the perspective of model design logic, this method integrates job market signals, on-campus training process and employment and entrepreneurship feedback into the same computing framework, realizes the transformation from single-point matching to full-cycle linkage prediction, and also provides a unified data basis for the position-capacity-resource collaborative modeling in the subsequent precision recommendation system.

3.2 Job demand feature representation learning and model optimization strategy

In the task of full-cycle employment demand prediction, the job demand is not a single text

label, but a compound semantic object composed of job title, job description, skill requirements, educational threshold, regional industry attributes and release time. If the job information is only represented by keyword statistics or bag-of-words vectors, the model often can only recognize high-frequency words on the surface, and it is difficult to distinguish between jobs such as "data analysis engineer" and "business analysis specialist", which have similar words but different ability focuses. Based on this, this paper divides the learning of job demand characteristics into four links: "original job data collation - multi-granularity semantic coding - structured attribute mapping - optimization training", and its processing flow is shown in Figure 2.

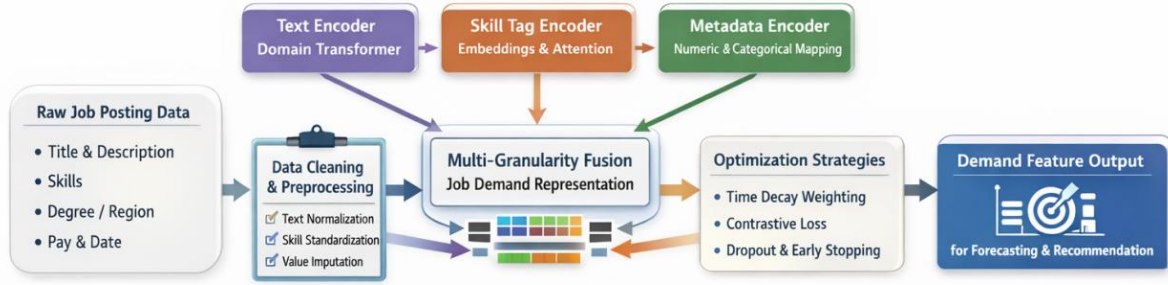


Figure 2: Flow chart of job demand feature representation learning and model optimization

In this study, a total of 84216 valid job samples were collected from the employment service platform, public recruitment website and school-enterprise cooperation job database of a regional university, and the time span was from January 2021 to December 2024. Each sample contains fields such as job title, job responsibility, skill requirements, educational requirements, industry category, work location, salary range, and release time. In order to ensure the input consistency, the system first cleans the job text by word segmentation, consolidates synonymous skills, standardizes terms, fills missing fields, and establishes the job skill vocabulary \mathcal{V}_s and industry category mapping table \mathcal{V}_c . For any job sample p_i , its original input is denoted by:

$$p_i = \{T_i, S_i, M_i, \tau_i\} \quad (5)$$

where T_i is the post text sequence, S_i is the set of skill labels, M_i is the structured attributes such as educational background, industry, region and salary, and τ_i is the timestamp information.

In the feature representation stage, the job responsibility and job requirement texts are encoded by a domain-adaptive Transformer to obtain the context semantic matrix $H_i^t \in \mathbb{R}^{L \times d}$. The skill labels are mapped into a skill vector matrix $H_i^s \in \mathbb{R}^{K \times d}$ by the embedding layer, and the job skill summary is obtained by attention aggregation. Structural attributes are mapped to meta-feature vector h_i^m by numerical normalization and category embedding. The three types of features are fused according to a unified dimension to form the job demand representation:

$$h_i = [h_i^t; h_i^s; h_i^m] \in \mathbb{R}^{3d} \quad (6)$$

Among them, the text summary vector h_{ij}^t is obtained by attention pooling:

$$\alpha_j = \frac{\exp(q^T h_{ij}^t)}{\sum_{u=1}^L \exp(q^T h_{iu}^t)}, h_i^t = \sum_{j=1}^L \alpha_j h_{ij}^t \quad (7)$$

The mechanism can automatically highlight more discriminative segments such as "core skills", "business scenarios" and "experience constraints" in long texts, and reduce the noise interference caused by template expression.

Considering the obvious long-tail phenomenon of job distribution in the job market, this paper introduces a joint strategy of time decay weighting and class balance in the model optimization. A more recent sample of jobs is given a higher weight to increase the sensitivity of the model to recent changes in the market:

$$\omega_i = \exp(-\lambda(t_{\text{now}} - \tau_i)) \quad (8)$$

In the design of loss function, the demand prediction loss, the representation constraint loss and the regularization term are incorporated into the training objective:

$$\mathcal{L} = \beta_1 \sum_i \omega_i \mathcal{L}_{\text{pred}}(y_i, \hat{y}_i) + \beta_2 \mathcal{L}_{\text{con}} + \beta_3 \|\Theta\|_2^2 \quad (9)$$

\mathcal{L}_{con} is used to narrow the representation of similar jobs and distance heterogeneous jobs, so as to improve the clarity of the semantic boundary of jobs. In the training process, Dropout, early stopping mechanism and adaptive learning rate scheduling are combined to reduce the problem of over-fitting of popular jobs and insufficient identification of unpopular jobs.

3.3 Employment demand forecast output mechanism and deployment adaptability design

In order to make the model results directly enter the "recruit, train and create" collaborative link, this paper does not stop at the single probability output level for employment demand prediction, but constructs a structured result generation mechanism for business calls. For any professional direction or job cluster g , the system simultaneously outputs four types of results: demand intensity, growth trend, capacity gap and forecast confidence to form a unified forecast vector:

$$\mathbf{o}_g = [d_g, \Delta_g, q_g, c_g] \quad (10)$$

Among them, d_g represents the intensity of job demand in the future cycle, Δ_g represents the rate of demand change under adjacent time Windows, q_g represents the degree of gap obtained compared with the current student ability profile, and c_g represents the stability judgment of the model on the prediction result. The purpose of this process is to put "what the market needs" and "what students still lack" in the same output plane, so that the recommendation module in Chapter 4 can directly perform job push, course compensation and training resource allocation. Considering that the job market has obvious volatility, this paper adds a forecast calibration mechanism to the output. Let the original output of the model be z_g , then the confidence probability after temperature scaling can be expressed as follows.

$$p_g = \frac{\exp(z_g/\tau)}{\sum_k \exp(z_k/\tau)} \quad (11)$$

where, τ is the calibration temperature parameter. This process can alleviate the overconfidence problem of the deep model in popular jobs, and make the prediction results of high-frequency jobs and unpopular jobs more comparable in the business end. At the same time, in order to enhance the response ability of the system to demand mutation, this paper defines the demand early warning index:

$$r_g = \eta_1 d_g + \eta_2 \Delta_g + \eta_3 q_g \quad (12)$$

When r_g exceeds the threshold, the system automatically marks the corresponding job cluster as the focus object, and triggers the rearrangement of resources on the training side and the update of the recommendation strategy.

At the deployment level, this paper adopts a combination of "offline training + incremental update + online service". In the offline stage, the historical job data, student growth data and employment feedback data were used to complete the model training and parameter solidification. In the incremental stage, new recruitment texts, course score changes and internship feedback were received weekly, and the job representation database and demand index were partially refreshes. In the online stage, millisecond query results are provided to the career guidance end, the department management end and the student server through the lightweight reasoning interface. In order to ensure the deployment stability in different hardware environments, the system splits text encoding, relational reasoning and result generation into independent services, which are encapsulated by containerization, and caches high-frequency job cluster representations through batch reasoning to reduce repeated calculation overhead.

In addition, this paper sets the deployment adaptability index to measure the model practicality. If the size of a single batch of requests is n , the average response latency is T_{avg} , and the servability is defined as follows.

$$A = \frac{n}{T_{avg} + \epsilon} \quad (13)$$

where ϵ is a tiny constant that prevents the denominator from being zero. This metric is not directly involved in the training, but can effectively reflect the throughput ability of the model in the real business environment. Therefore, the prediction module is no longer just an accuracy model in the experimental environment, but becomes the computing core that can stably support the full-cycle employment service linkage.

4 The construction of an accurate recommendation system for the full cycle of "recruiting, training and Creating"

4.1 Correlation modeling of job requirements, user capabilities and training resources

The key to the establishment of accurate recommendation is not whether the information of positions, students and courses exist at the same time, but whether the three information can be organized into a computable, updatable and callable association structure. For the full-cycle scenario of "recruiting training for creation", job demand has dynamic fluctuation characteristics, user capabilities show stage accumulation and differentiation, and training resources include various types of courses, projects, competitions, practical training, entrepreneurial training and guidance services. If the static management method of "post database, student database and course database" is still separated from each other, the recommendation results often only stay at a shallow similar matching, and it is difficult to answer why students are suitable for a certain type of position, what ability dimensions are the current gaps, and what resources should be completed. Based on this, this paper constructs a ternary association model of job demand-user capability-training resources, and converts the

prediction results into graph structure semantic relations, whose overall structure is shown in Figure 3. In this paper, the core object in the system is represented as a heterogeneous graph $G=(V,E,R)$, where the node set $\mathcal{V} = \mathcal{V}^J \cup \mathcal{V}^U \cup \mathcal{V}^R$ represents the post node, user node and resource node respectively. The edge set E is composed of multiple relationships such as "positions need skills", "users have capabilities", "resources improve capabilities" and "resources are position-oriented". R denotes the set of relation types. In order to avoid inconsistent terminology in different systems, this paper establishes a skill standard vocabulary and capability mapping rules, and combines expressions such as "Python development", "data processing" and "data cleaning" into reusable capability units, and assigns a unified code and timestamp to each node. After this process, the skill requirements extracted from the post text, the ability characteristics generated by the student process data, and the training resource labels can be aligned in the same semantic coordinate.

User capability modeling adopts dynamic accumulation method. For any user u , its capability state vector at time t is denoted by:

$$a_u^{(t)} = \phi(W_1x_u^{\text{adm}} + W_2x_u^{\text{learn}} + W_3x_u^{\text{prac}} + W_4x_u^{\text{innov}}) \quad (14)$$

where, x_u^{adm} represents the basic profile formed in the enrollment stage, x_u^{learn} represents the course learning characteristics, x_u^{prac} represents practice and internship experience, x_u^{innov} represents the innovation and entrepreneurship participation information, and $\phi(\cdot)$ is a nonlinear mapping function. Job demand node j generates demand vector b_j by responsibility text, skill label and market trend, and training resource node r generates supply vector c_r by resource content, training target and applicable object. Based on this, the system calculates the capability gap between the user and the position:

$$g_{u,j} = \left\| \text{ReLU}(b_j - a_u^{(t)}) \right\|_1 \quad (15)$$

This formula reflects the part of the target position requirements that has not been covered by the current capacity, and the larger the value is, the stronger the compensation demand is. In order to make the recommendation not only stay in the static matching of "person and post", this paper further introduces a resource bridging scoring mechanism to measure the contribution of a training resource to narrowing the capacity gap:

$$s_{u,j,r} = \mu \text{sim}(a_u^{(t)}, c_r) + \nu \text{sim}(c_r, b_j) - \xi g_{u,j} \quad (16)$$

where $\text{sim}(\cdot)$ denotes cosine similarity, μ, ν, ξ are weight parameters. The scoring considers the suitability of resources and students' current status, the consistency of resources and target job requirements, and the original gap size, so that it can unify "what is suitable to learn" and "what can be filled after learning". The output of the model is not a single point matching score, but an association chain that is led by the position goal, based on the ability difference, and undertaken by specific resources.

As shown in Figure 3, after the three-layer model is built, the system can store the nodes and relationships into the graph database, and open to the employment guidance end, the department training end and the student personal end through the recommendation service interface. In this way, the job demand prediction results no longer stay at the analysis report level, but are transformed into a searchable, interpretable, and interactional association network, which lays a structural foundation for the realization of the subsequent personalized accurate recommendation mechanism.

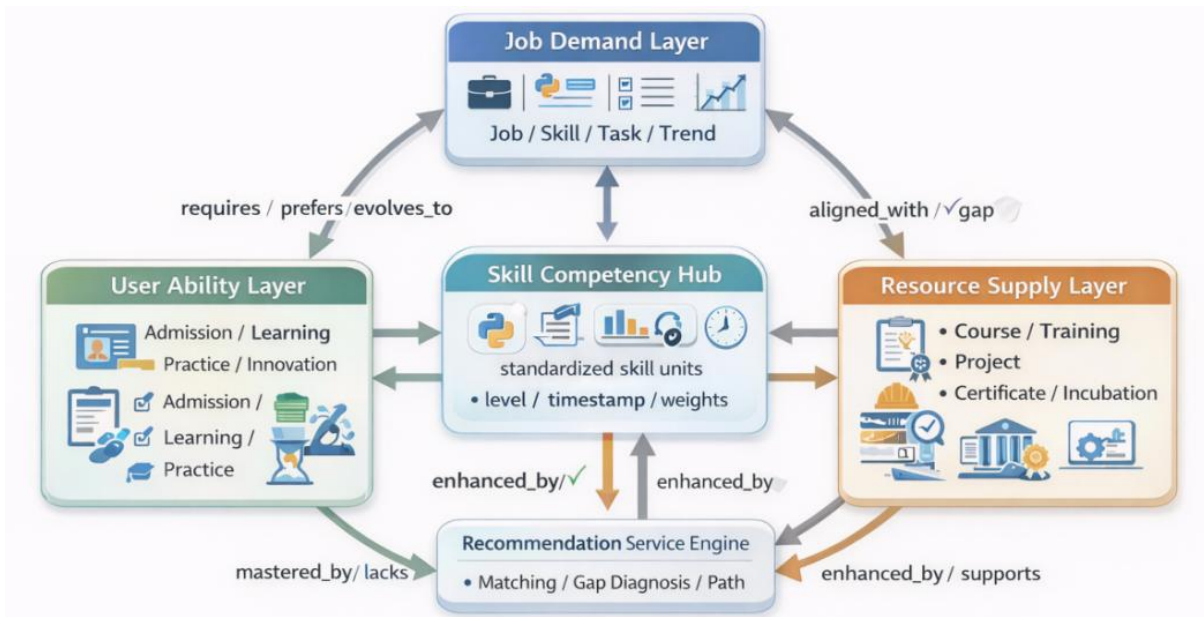


Figure 3: Modeling structure diagram of relationship among post requirements, user capabilities and training resources

4.2 Personalized and accurate recommendation mechanism design for recruitment, training and innovation collaboration

After the correlation modeling of job requirements, user capabilities and training resources is completed, the core problem of the recommender system is transformed into: how to generate a personalized program that can simultaneously serve enrollment guidance, training intervention, employment matching and entrepreneurial support according to the user's stage, ability change trajectory and job market fluctuations. If the recommendation still stays at the ranking level of a single position, the system can provide a number of similar positions, but it is difficult to answer "why recommended", "where is the short board" and "what should be fixed next". Based on this, this paper constructs a personalized accurate recommendation mechanism for the collaboration of "recruit training and Innovation". Its process consists of four modules: state perception, collaborative scoring, policy distribution and dynamic feedback, and the overall structure is shown in Figure 4.

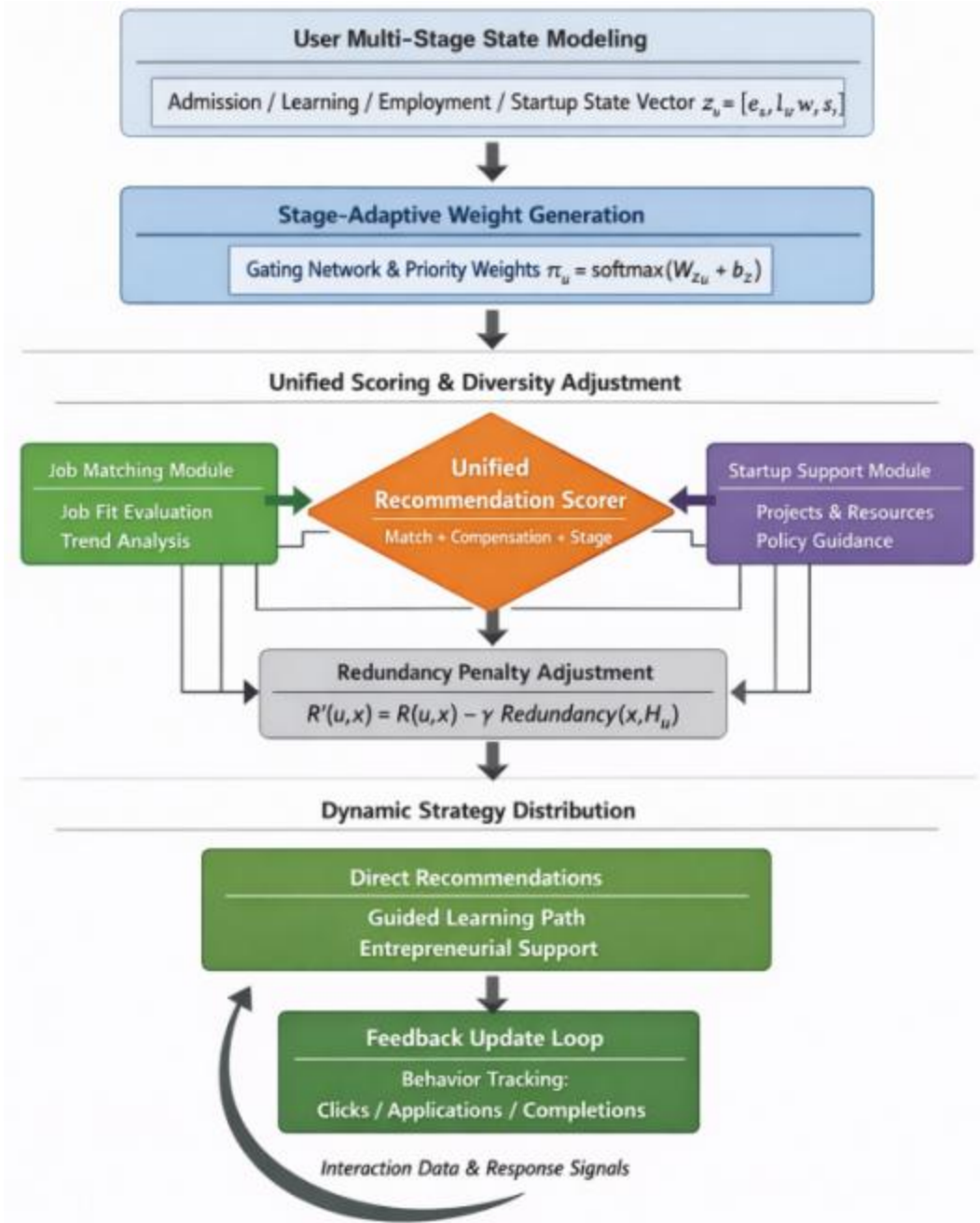


Figure 4: Personalized accurate recommendation mechanism for recruiting training and innovation collaboration

The system first identifies the user's current stage. For any user u , let its phase state vector be

$$z_u = [e_u, l_u, w_u, s_u] \quad (17)$$

Among them, e_u represents the interest and basic characteristics formed in the enrollment stage, l_u represents the learning input and course completion in the training stage, w_u represents the employment readiness and the intensity of job search behavior, and s_u represents the participation in innovation and entrepreneurship. Based on this state vector, instead of calling the same recommendation template for all users, the model generates stage weights via a gating function:

$$\pi_u = \text{softmax}(W_z z_u + b_z) \quad (18)$$

Therefore, the individual preference distribution for the four goals of recruitment, training, employment and creation is obtained. For lower grade students, the system will improve the weight of training resources and post cognitive content. For students approaching graduation, the priority of job matching, internship recommendation and ability compensation advice should be enhanced. For users with entrepreneurial tendencies, the proportion of project resources, policy information and entrepreneurial mentor matching will be increased simultaneously.

In the recommendation calculation layer, this paper combines the job fitness, resource compensation and stage consistency to construct a comprehensive scoring function. For candidate x (which can be a position, course, training program or entrepreneurial resource), the final recommendation score is defined as follows.

$$R(u, x) = \rho_1 f_{\text{match}}(u, x) + \rho_2 f_{\text{comp}}(u, x) + \rho_3 f_{\text{stage}}(u, x) \quad (19)$$

Among them, f_{match} describes the degree of semantic adaptation between the user and the candidate object, f_{comp} measures the compensation strength of the object to the shortboard of ability, and f_{stage} determines whether it conforms to the task of the current stage. In order to avoid the recommendation results being too concentrated on hot jobs or high-frequency resources, the system introduces a diversity adjustment item:

$$R'(u, x) = R(u, x) - \gamma \text{Redundancy}(x, \mathcal{H}_u) \quad (20)$$

where \mathcal{H}_u represents the user's history of receiving and interacting records, and $\text{Redundancy}(\cdot)$ is used to penalize objects that are excessively repeated with previous recommendations. In this way, the local shrinkage problem of "the more points are narrower" can be alleviated, so that the recommendation list remains both targeted and reasonable exploration space. In order to realize collaborative service, the system designs three types of recommendation paths at the output side. One is direct recommendation for job matching, which outputs suitable positions, demand changes and delivery priorities. One is the path recommendation for training compensation, which outputs the combination scheme of courses, certificates, competitions and practical training. The other is support and recommendation for entrepreneurial transformation, and output projects, mentors, policies and incubation resources.

4.3 Recommendation result analysis and interactive service implementation

After the calculation of personalized recommendation, the system still needs to solve a problem closer to the application, that is, how to transform the model output into understandable, operable and sustainable feedback service results. If the platform only returns the job list or resource ranking, although the user can see the recommended object, it is difficult to judge the recommendation basis and form follow-up actions based on it. Based on this, this paper designs the recommendation result analysis and interactive service implementation as a continuous process of "result explanation-interface presentation-behavior feedback-strategy update", so that job recommendation, ability diagnosis and training advice are coordinated in the same service link.

In the result analysis layer, the system no longer directly displays a single matching score, but synchronously outputs four types of information, including job suitability, capacity gap

intensity, resource compensation direction and market demand heat, and generates an explanation vector:

$$e_{u,x} = [m_{u,x}, d_{u,x}, b_{u,x}, h_x] \quad (21)$$

where, $m_{u,x}$ represents the matching degree between the user and the candidate object x , $d_{u,x}$ represents the current ability gap, $b_{u,x}$ represents the expected contribution of the recommended object to the compensation of the short board, and h_x represents the demand heat of the job or resource in the current cycle. This vector is used to drive the front-end explanation module, so that the user can see "why recommended", "what is missing", "what is needed", and "is it worth the priority investment now" at the same time.

In the interactive service layer, the system constructs three kinds of interfaces: job recommendation view, ability diagnosis view and resource path view. The job recommendation view shows the target position, demand change and delivery priority. The capability diagnosis view maps the skill coverage to a visual radar chart or hierarchical strip. The resource path view suggests a combination of courses, training, competitions, certificates and entrepreneurial support. As shown in Table 2, each module does not run separately, but is scheduled by the unified recommendation service interface. The front-end receives structured results and displays them hierarchically, while the back-end supports high-frequency access through graph database retrieval, cache queue and log service.

Table 2: Recommendation result analysis and interactive service module design

Module Name	Core Inputs	Main Functions	User-Visible Outputs
Job Recommendation Module	Job demand prediction results, user competency profile	Generates job ranking, displays demand trends and application priority	Recommended job list, popularity indicators, matching explanations
Competency Diagnosis Module	Skill vectors, competency gap results	Analyzes existing competencies and identifies competencies to be improved	Skill coverage map, weakness alerts, improvement directions
Resource Pathway Module	Course database, training projects, certificate resources, entrepreneurship support data	Generates staged compensation and growth pathways	Course recommendations, training plans, entrepreneurship resource packages
Behavioral Feedback Module	Clicks, bookmarks, applications, registrations, completion records	Updates user status and recommendation weights	Refreshed personalized results, adjusted recommendation explanations

In order to improve the response ability of the system to user behavior, this paper introduces an online feedback update mechanism on the server. Suppose the user's feedback signal to the recommended object at time t is r_t , and the model's estimate of this feedback is \hat{r}_t . Then the parameter update can be expressed as follows.

$$\Theta_{t+1} = \Theta_t + \alpha(r_t - \hat{r}_t)\nabla_{\Theta} \log P(x_t|u_t) \quad (22)$$

Here, α is the learning step size. This mechanism can continuously stream the click, collection, registration, delivery, completion of learning and other behaviors back to the recommendation engine, so that the system can gradually revise the judgment of the user's stage goals and real preferences. As a result, the recommendation service is no longer a static result output, but a dynamic support platform that can be adjusted over time.

5 System implementation and experimental evaluation

5.1 Full-cycle employment service system architecture and functional module implementation

In order to test whether the model built in the previous section can operate stably in the real business scenario, this paper further realizes the employment service system for the full cycle of "recruit training and create". The system adopts a hierarchical architecture, and organizes data access, model reasoning, association retrieval, recommendation service and interactive feedback into a unified link, instead of deploying job prediction, ability diagnosis and resource recommendation separately. On the whole, the platform was composed of data layer, computing layer, service layer and application layer. The data layer accessed multi-source data of enrollment system, educational administration system, competition practice platform, employment management platform and innovation and entrepreneurship platform. The job demand prediction model, ability representation model and recommendation ranking model were deployed in the computing layer. The service layer provides interfaces for portrait update, graph retrieval, recommendation interpretation and log reflux. The application layer provides differentiated services for the student end, teacher end and management end.

The backend of the system uses Python 3.11 and FastAPI as the core framework, the model reasoning part is deployed by PyTorch, the relationship retrieval is completed by Neo4j, the business data is stored in MySQL, and the high-frequency portrait and recommendation results are cached through Redis. The front-end uses Vue 3 and ECharts to realize the job popularity panel, ability shortboard view and resource path view, so that the prediction results can be presented in a readable way. In order to improve the degree of module decoupling, the system uses JSON interface to transmit data, and uses Docker to complete service encapsulation and version isolation. In the runtime environment, the platform is deployed on an Ubuntu 22.04 server with 12 CPU cores, 64 GB memory and an RTX 4090 GPU, which can support offline training, incremental updating and online inference at the same time.

In terms of function implementation, the system has completed five core modules: job demand monitoring, student ability portrait generation, personalized recommendation, resource path planning and behavior feedback update. The test shows that the system can complete the incremental synchronization of about 126,000 posts and behavior data every day, the average time of single job demand prediction is 41 ms, and the average time of single user recommendation result generation is 58 ms. Under the condition of 200 concurrent requests, the successful response rate of the interface reaches 99.3%. 95% of these requests had a return time of less than 230 ms. After the caching mechanism is put into operation, the recomputation overhead in the high-frequency query scenario is reduced by 31.7%. As shown in Table 3, each module has formed a clear division of labor in terms of input objects, output results and operation performance, which indicates that the system has the basic realization ability to support the linkage of regional colleges and universities' employment services and intra-school business collaboration.

Table 3: Main modules and operation results of full-cycle employment service system

Module Name	Main Inputs	Main Outputs	Key Technologies	Operational Results
Multi-source Data Integration Module	Admissions, course, internship, employment, and entrepreneurship data	Standardized thematic data tables	ETL, field mapping, data cleaning	Average daily synchronization of 126,000 records
Employment Demand Prediction Module	Job texts, industry trends, historical recruitment records	Job demand intensity and changing trends	Transformer, time-series forecasting	41 ms per prediction
User Competency Profiling Module	Grades, competitions, certificates, practical behavior data	Dynamic competency vectors and skill-gap lists	Representation learning, feature fusion	Profile update in 1.8 s per 1,000 users
Precision Recommendation Module	Job demand, user profiles, resource tags	Job ranking and training pathway recommendations	Graph retrieval, learning to rank	58 ms recommendation per user
Interactive Feedback Module	Clicks, bookmarks, applications, registration records	Weight updates and strategy adjustment	Redis, log feedback, incremental updating	Concurrent success rate of 99.3%

5.2 Employment demand forecasting performance test and result analysis

In order to test the prediction ability of the constructed model in the real "recruit training to create" scenario, this paper carried out a comparative experiment around the identification task of employment demand intensity. The experimental data comes from 84216 job records collected and cleaned from January 2021 to December 2024, and 18274 student training process records and 6315 internship and employment feedback records are jointly accessed. 38760 valid samples were generated according to the monthly sliding window and the job cluster mapping rule. In this paper, the state of job demand in the future cycle is divided into five categories: high growth, growth, stability, decline and low demand. The data set is divided into training set, validation set and test set according to 8 : 1 : 1. The experimental environment is consistent with Section 5.1, the training framework is PyTorch, the optimizer adopts AdamW, the initial learning rate is set to 2×10^{-5} , the batch size is 32, the maximum training round is 40, and the early stopping strategy is set to suppress overfitting.

The comparison models include XGBoost, BiLSTM, Transformer, Transformer+GRU, and the full-cycle fusion model proposed in this paper. The evaluation indexes are Accuracy, Macro-F1 and Top-3 hit rate. Among them, the Top-3 hit rate is used to measure whether the real demand category falls into the Top three candidates of the model output, which is closer to the actual demand of the "focus on job cluster" screening in the employment service scenario. The

experimental results show that the traditional tree model has certain stability in structural features, but its ability to describe the semantic changes of post text and cross-stage data association is limited. Sequence models are better at recognizing temporal evolution features, while Transformers are better at semantic understanding. In contrast, the proposed model achieves the best results in terms of comprehensive indicators, indicating that the joint modeling of job texts, training sequences and heterogeneous relationship information indeed improves the discriminative ability of demand forecasting.

As shown in Figure 5, the Accuracy of the proposed model reaches 89.3%, which is 9.9, 6.6 and 4.4 percentage points higher than that of XGBoost, BiLSTM and Transformer, respectively. Macro-F1 reached 88.1%, indicating that the model was more balanced in the identification of different demand levels, and was not significantly biased towards high-frequency categories. The Top-3 hit rate reaches 95.6%, which shows that the system has strong practical value in the job demand early warning and key direction screening. It is worth noting that the performance of Transformer+GRU has been significantly better than that of the single channel model, which indicates that text semantic or simple temporal information is not enough to support full-cycle prediction tasks, and cross-time and cross-subject information fusion is the key source of performance improvement.

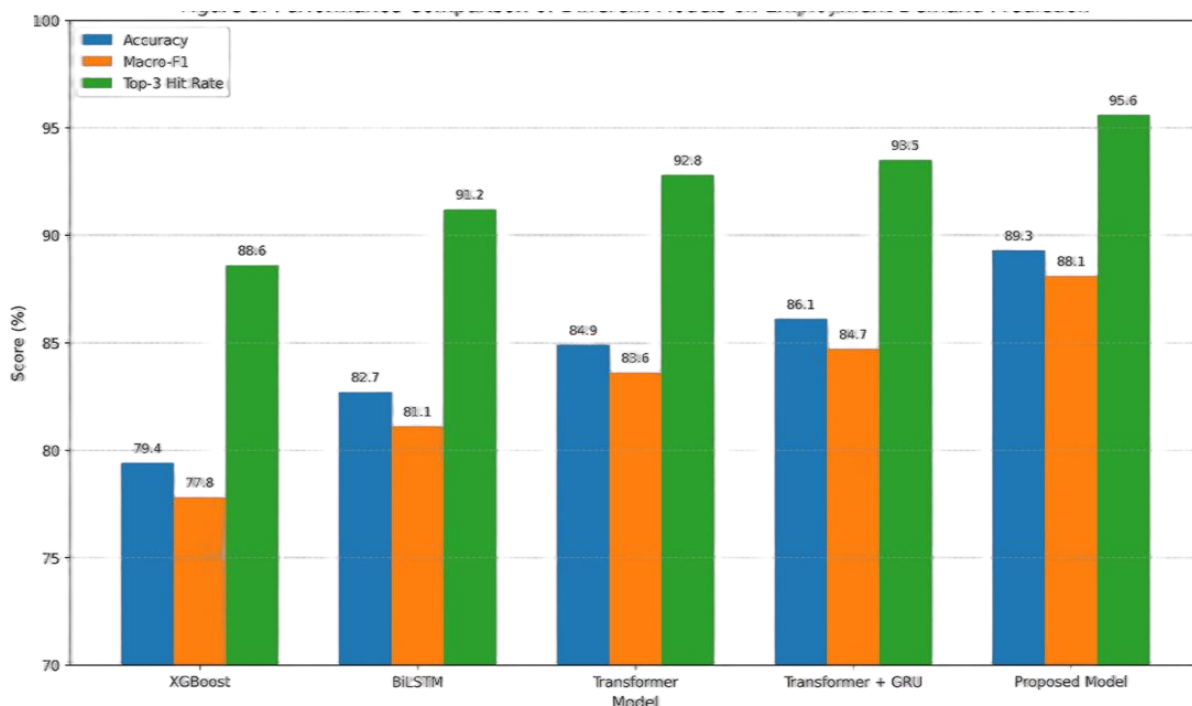


Figure 5: Performance comparison of different models on the employment demand prediction task

In order to further analyze where the model gain comes from, this paper conducts ablation experiments on feature input, and investigates four Settings: post text features, post text and training sequence features, post text and training sequence plus heterogeneous relationship features, and the complete model. The results are shown in Figure 6. It can be seen that when only using the post text, although the model can identify the semantic differences of the post, the perception of the training process and ability accumulation in the school is insufficient, with an Accuracy of 84.9% and an RMSE of 0.161. After adding the training sequence, the model grasps the coupling relationship between demand change and capacity supply more fully, the Accuracy is increased to 87.0%, and the RMSE is reduced to 0.143. After adding the

heterogeneous relationship, the communication structure between position-skills-course-students was supplemented, and the performance continued to improve. The complete model achieves 89.3% Accuracy, 88.1% Macro-F1 and 0.127 RMSE, indicating that multi-source heterogeneous data are not simply stacked, but form complementary prediction signals in a unified representation space.

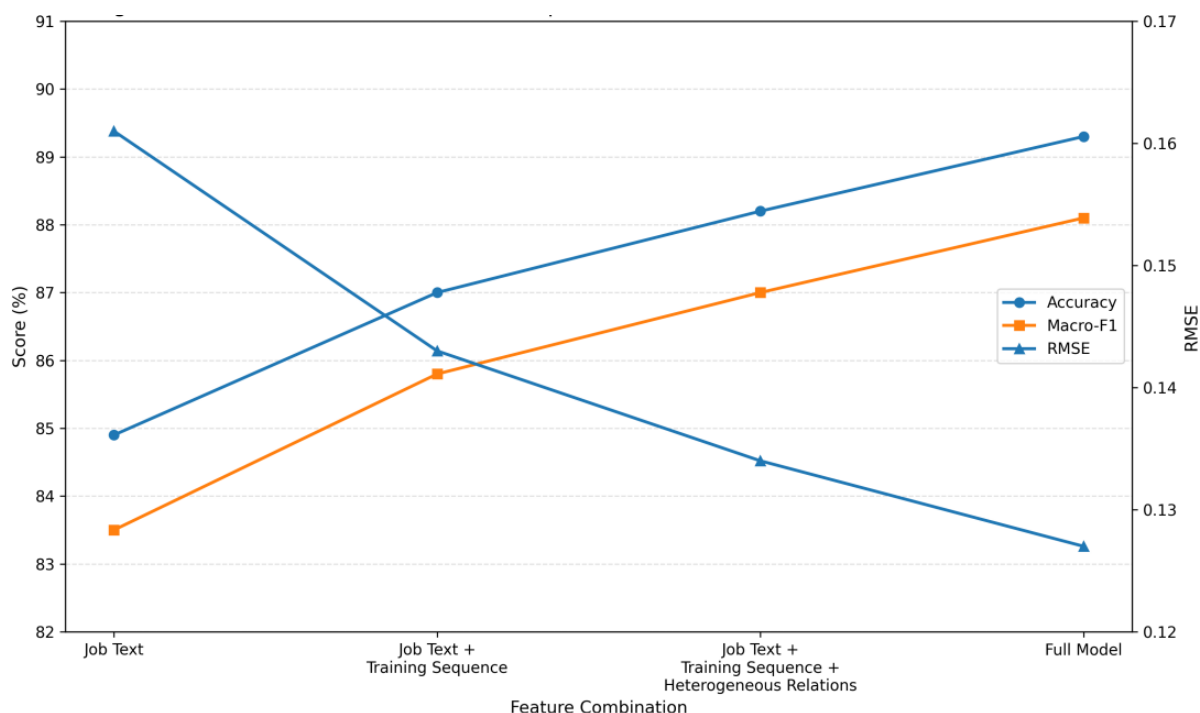


Figure 6: Performance variation of the proposed model under different feature combinations

On the whole, the experiments in this section verify two points. On the one hand, if the employment demand forecast is separated from the training process and ability structure, it can only obtain relatively rough market judgment. On the other hand, after the heterogeneous data in the "recruit, train and create" chain are incorporated into the unified model, the system can not only more accurately predict the change of job demand, but also provide a more stable input basis for subsequent accurate recommendation. This also lays the result support for the recommendation effect evaluation in Section 5.3.

5.3 Accurate recommendation effect and application feedback evaluation

In order to verify the effectiveness of the constructed system in real application scenarios, this paper carried out application tests for 8 consecutive weeks after the system was deployed. The test objects cover four types of core user groups, which are student users, teachers, employment managers and innovation and entrepreneurship guidance personnel, with a total of 168 people, including 96 students, 28 teachers, 24 employment managers and 20 entrepreneurial guidance personnel. The evaluation process is based on the actual operation interface of the platform. The system synchronously records the user's browsing, clicking, bookmarking, Posting, registration and feedback submission behavior logs, and measures the recommendation related experience with a 5-point scale. Considering that the focus of this study is not only "accuracy", but also whether the results are easy to understand and whether they can support follow-up actions, the evaluation dimensions are set as four items: recommendation relevance, result interpretability, path operability and comprehensive satisfaction.

In the experiment implementation, the student end mainly received job recommendation, ability shortboard diagnosis and resource compensation path. The teacher side mainly checked the class ability distribution, post demand changes and curriculum support suggestions. The employment management end focuses on the use of demand early warning, job cluster heat analysis and person-post matching kanban board. The entrepreneurial guidance end uses more project direction recommendation, entrepreneurial resource docking and high-potential student identification functions. In the background of the system, the log analysis module plays back the operation links of different roles, and tracks whether the recommendation results trigger subsequent actions. Statistical results show that 72.8% of all test samples have at least one effective follow-up behavior after receiving the recommendation, of which the job click conversion rate of the student side is 38.6%, and the registration rate of courses or training resources is 31.4%, which are 12.3 and 10.7 percentage points higher than those before using the recommendation service.

As shown in Table 4, all the four types of users gave high evaluations of the system performance, but their focus was different. Student users had the highest scores on recommendation relevance and path operability, reaching 4.51 and 4.47 respectively, indicating that the suggestions for post and ability improvement given by the system were closer to the actual state of individuals. Teacher users have a high evaluation on the interpretability of the results, reaching 4.42, indicating that the ability shortboard identification and resource association logic have good teaching readability. The comprehensive satisfaction of employment managers reached 4.58, which reflected that the demand prediction results had a strong supporting role in job organization, key group identification and service arrangement. The overall score of entrepreneurial mentors was slightly lower than that of other groups, but their evaluation on the effectiveness of entrepreneurial resource matching still reached 4.29, indicating that the system had a certain ability of "innovation linkage", but there was still room for improvement in cross-project opportunity discovery and long-term tracking.

Table 4: Application feedback evaluation results for different user groups

User Group	Recommendation Relevance	Result Interpretability	Path Operability	Overall Satisfaction
Student Users	4.51	4.36	4.47	4.49
Teacher Users	4.33	4.42	4.28	4.37
Employment Management Staff	4.46	4.51	4.54	4.58
Entrepreneurship Advisors	4.21	4.18	4.24	4.26

From the behavioral data, the advantage of the system is not only reflected in the static score, but also in the compression effect of interactive links. Figure 7 shows the changes of several key application indicators before and after the recommendation service investment. It can be seen that the average decision time from entering the system to completing the first effective delivery is reduced from 26.4 minutes to 18.7 minutes, with a decrease of 29.2%. The time required for teachers to locate the shortcoming of key ability decreased from 14.1 min to 9.3 min; The average processing time for employment managers to complete job screening and clustering services decreased from 32.8 minutes to 21.6 minutes. The above changes show that the recommendation system does not stay at the level of "result display", but substantially improves the efficiency of information positioning and service collaboration.

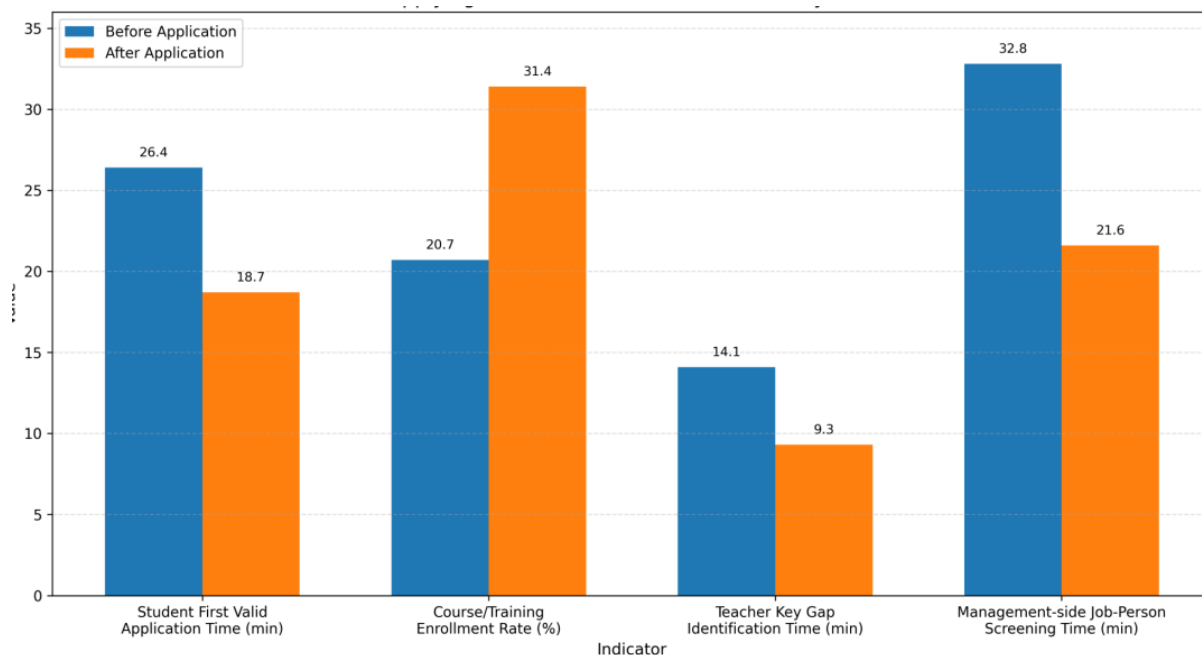


Figure 7: Comparison of key service indicators before and after the application of the precision recommendation system

On the whole, the application feedback shows that the accurate recommendation system constructed in this paper has good practicability in job matching, ability diagnosis and resource path generation. More importantly, the demand change results output by the prediction module can be effectively absorbed by the recommendation module and transformed into executable suggestions through interactive services, forming a closed loop from data perception to service feedback. At the same time, the score differences of the entrepreneurial guidance group also suggest that it is still necessary to strengthen the entrepreneurial opportunity graph expansion, project similarity recognition and long-term feedback modeling in the future, so as to further improve the full chain collaboration level of "recruiting and training for innovation".

6 Conclusion and Prospect

Focusing on the full-cycle collaborative needs of "recruiting and training for creation", this paper constructs an integrated intelligent system composed of enrollment portrait integration, training process modeling, employment demand prediction, linkage recommendation of entrepreneurial resources and interactive feedback services. The research included 84216 job records, student training process data, internship employment feedback and innovation and entrepreneurship information into the unified computing framework, and realized cross-stage linkage analysis through deep learning and heterogeneous correlation modeling. The experimental results show that the Accuracy of the proposed employment demand prediction model reaches 89.3%, the Macro-F1 is 88.1%, and the Top-3 hit rate is 95.6%. In the application test involving 168 real users, the proportion of effective follow-up behaviors triggered after recommendation reached 72.8%, and the decision time of students' first effective delivery was reduced from 26.4 minutes to 18.7 minutes, indicating that the system can not only accurately identify the change of job requirements. It can also transform the prediction results into executable training compensation and job recommendation programs.

At the same time, it should be noted that the current research still has some limitations. Firstly, the sample sources are mainly regional job data and business data on campus, and the

coverage of long-tail jobs across regions and industries is still insufficient. Second, although the model has taken into account both prediction accuracy and deployment efficiency, there is still room for improvement in the adaptability to sudden market fluctuations and extremely low frequency emerging jobs. Thirdly, the recommendation feedback mainly comes from the explicit behavior of the platform, which has not yet fully absorbed the reverse correction effect of long-term career development results on the model.

The follow-up research can be carried out in three directions: first, expand multi-regional and multi-industry data access to enhance the time-varying generalization ability of demand forecasting; Secondly, the graph neural network, contrastive learning and incremental update mechanism were introduced to improve the recognition effect of new occupations and composite skill sets. Thirdly, the closed-loop modeling of "recommendation-learning-employment results" was strengthened, so that the system was further developed from a short-term matching tool to a continuous optimization platform for the whole process of talent training.

Funding

This work was supported by (This work was supported by (Project 1: Major Project of the 2025 Special Research on Employment and Entrepreneurship in Henan Province, with a funding of 100,000 RMB, titled "Research on the Integration of Specialization and Innovation and the Construction of High-Quality Talent Cultivation System in Application-Oriented Universities", Grant No. CJHZX25004; Project 2: Key Project of the Teaching Reform Research and Practice Project of Pingdingshan University, titled "Research and Practice on the Whole-Cycle 'Recruitment-Training-Employment-Innovation & Entrepreneurship' Integrated Education Model Integrating Specialization and Innovation in Application-Oriented Universities Empowered by AI", Grant No. 2025-JYZD01)).

References

- [1] Mashayekhi Y, Li N, Kang B, et al. A challenge-based survey of e-recruitment recommendation systems[J]. *ACM Computing Surveys*, 2024, 56(10): 1-33.
- [2] Kumar D, Grosz T, Rekabsaz N, et al. Fairness of recommender systems in the recruitment domain: an analysis from technical and legal perspectives[J]. *Frontiers in big Data*, 2023, 6: 1245198.
- [3] Yao K, Zhang J, Qin C, et al. Knowledge enhanced person-job fit for talent recruitment[C]//2022 IEEE 38th International Conference on Data Engineering (ICDE). IEEE, 2022: 3467-3480.
- [4] Wang Z, Wei W, Xu C, et al. Person-job fit estimation from candidate profile and related recruitment history with co-attention neural networks[J]. *Neurocomputing*, 2022, 501: 14-24.
- [5] Huang Y, Liu D R, Lee S J. Talent recommendation based on attentive deep neural network and implicit relationships of resumes[J]. *Information Processing & Management*, 2023, 60(4): 103357.
- [6] Kokkodis M, Ipeiritis P G. The good, the bad, and the unhirable: Recommending job

- applicants in online labor markets[J]. *Management Science*, 2023, 69(11): 6969-6987.
- [7] Brek A, Boufaïda Z. AnnoJOB: semantic annotation-based system for job recommendation[J]. *Acta Informatica Pragensia*, 2023, 12(2): 200-224.
- [8] Chen H, Du L, Lu Y, et al. Professional network matters: Connections empower person-job fit[C]//*Proceedings of the 17th ACM International Conference on Web Search and Data Mining*. 2024: 96-105.
- [9] Cao Y, Chen X, Du L, et al. TAROT: A hierarchical framework with multitask co-pretraining on semi-structured data towards effective person-job fit[C]//*ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2024: 12046-12050.
- [10] Guan Z, Yang J Q, Yang Y, et al. JobFormer: skill-aware job recommendation with semantic-enhanced transformer[J]. *ACM Transactions on Knowledge Discovery from Data*, 2024, 19(1): 1-20.
- [11] Akkasi A. Job description parsing with explainable transformer based ensemble models to extract the technical and non-technical skills[J]. *Natural Language Processing Journal*, 2024, 9: 100102.
- [12] Tzimas G, Zotos N, Mourelatos E, et al. From data to insight: Transforming online job postings into labor-market intelligence[J]. *Information*, 2024, 15(8): 496.
- [13] Weichselbraun A, Süsstrunk N, Waldvogel R, et al. Anticipating job market demands—a deep learning approach to determining the future readiness of professional skills[J]. *Future Internet*, 2024, 16(5): 144.
- [14] Senger E, Zhang M, Van Der Goot R, et al. Deep learning-based computational job market analysis: A survey on skill extraction and classification from job postings[C]//*Proceedings of the First Workshop on Natural Language Processing for Human Resources (NLP4HR 2024)*. 2024: 1-15.
- [15] Gnehm A, Bühlmann E, Buchs H, et al. Fine-grained extraction and classification of skill requirements in German-speaking job ads[C]//*Proceedings of the Fifth Workshop on Natural Language Processing and Computational Social Science (NLP+ CSS)*. 2022: 14-24.
- [16] Haque R, Quek A, Hasan M R. Classification Techniques Using Machine Learning for Graduate Student Employability Predictions[J]. *International Journal on Advanced Science, Engineering & Information Technology*, 2024, 14(1).
- [17] Luo J H, Zhong W. Graduates Employment Prediction Based on Deep Learning[C]//*Proceedings of the 2024 9th International Conference on Distance Education and Learning*. 2024: 162-166.
- [18] Frej J, Dai A, Montariol S, et al. Course recommender systems need to consider the job market[C]//*Proceedings of the 47th international acm sigir conference on research and development in information retrieval*. 2024: 522-532.

- [19] Yamashita M, Tran T, Lee D. Openresume: Advancing career trajectory modeling with anonymized and synthetic resume datasets[C]//2024 IEEE International Conference on Big Data (BigData). IEEE, 2024: 6697-6706.
- [20] Decorte J J, Van Haute J, Deleu J, et al. Career path prediction using resume representation learning and skill-based matching[J]. arXiv preprint arXiv:2310.15636, 2023.
- [21] Ong X Q, Lim K H. SkillRec: A data-driven approach to job skill recommendation for career insights[C]//2023 15th International Conference on Computer and Automation Engineering (ICCAE). IEEE, 2023: 40-44.