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Research on the Dynamic Identification and Coping Strategy Optimization of College Students 'Slow Employment Behavior under the background of digital Economy

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SUMMARY: *Under the background of digital economy, the slow employment behavior of college students shows the characteristics of platform and continuous. The traditional recognition methods relying on questionnaires, static records and manual judgment are difficult to reflect the change of job hunting status. This paper constructs a framework for dynamic identification and strategy optimization of slow employment, integrates data such as recruitment platform logs, on-campus employment records, resume text, job semantics, consultation interaction and ability portrait, and based on 84,560 behavior samples of 2436 students in 8 months, after missing repair, feature coding, normalization and sliding window segmentation, it constructs a framework for dynamic identification and strategy optimization of slow employment. Local pattern extraction, temporal dependence modeling and attention aggregation are used to realize state recognition, risk prediction and intervention recommendation. Experimental results show that the accuracy of the model is 93.4%, the F1 value is 91.3%, and the comprehensive response efficiency is improved by 16.7%, which can provide computational support for digital employment services in colleges and universities.*

KEYWORDS: *Digital economy; Slow employment of college students; Dynamic recognition; Policy optimization*

1 Introduction

The digital economy has reconstructed the recruitment communication mode and the employment service form of colleges and universities, and the behavior chain of college students has migrated to the platform environment. Job browsing, resume delivery, online evaluation, consultation interaction, interview feedback and contract confirmation continue to generate data, so that slow employment is no longer just a lag phenomenon in the statistics of graduation destination, but a dynamic behavior sequence that can be tracked, segmented and calculated. Digital platform records can describe the employment action intensity, feedback rhythm and job preference drift, which provides an entrance for slow employment identification.

The existing college employment analysis still relies on questionnaire collection, manual

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interviews and stage accounts, which can reflect the distribution and is difficult to show the change of job hunting status. Short-term stagnation, repeated browsing, low matching delivery and feedback interruption of students on the recruitment platform often have temporal characteristics, and it is difficult to form stable discrimination only by static indicators. Slow employment identification in digital economy scenarios needs to reconstruct the analysis framework, which maps behavior logs, text information and process signals into a trainable data representation space, and then identifies the state transition through a time series model to support intervention decisions.

Data modeling around student development trajectories provides the methodological foundation. Wang et al. used campus big data to predict career choice, indicating that there is a stable data association between learning experience and behavioral characteristics [1]. ElSharkawy et al. used machine learning methods to predict the employability of information technology graduates and verified the usability of structured employment features in classification tasks [2]. El Mrabet et al. constructed a supervised learning framework to analyze students' academic orientation, indicating that educational behavior data can support direction discrimination and decision-making inference [3]. Fahd et al. systematically sorted out the application of machine learning in the field of higher education and pointed out that student risk identification was shifting from result assessment to process identification [4]. Trakunphutthirak et al. carried out academic performance prediction based on incremental time data, which strengthened the value of time series in behavior evolution analysis [5]. Siswipraptini et al. proposed a personalized career path recommendation model and showed the realization path of linkage between recommendation mechanism and student portrait [6]. Song et al. used machine learning to construct group portraits of college students, which improved the expression ability of student behavioral heterogeneity [7]. Okoye et al. applied the ensemble model to the student retention rate and graduation prediction, indicating that multi-model fusion is beneficial to enhance the discriminant stability of complex educational data [8]. Vaarma et al. conducted an empirical study on student dropout prediction and proved that persistent behavioral signals have high explanatory power for risk early warning [9].

These studies provide reference ideas for the calculation of employment behavior, but the slow employment of college students still has modeling characteristics other than academic prediction and career recommendation. Slow employment is not a single label, but a state formed by the willingness to seek employment, skill preparation, information acquisition, feedback waiting and decision delay. The relevant data include platform interaction logs, resume texts, job descriptions and consultation records, which are heterogeneous in type and scale. Without unified coding and time alignment, the recognition results are easy to stay at the surface level. University employment service pays more attention to whether the identification results can be transformed into executable strategies, so the model not only needs to output the risk level, but also needs to give the basis for job recommendation and consultation intervention.

Based on the above background, this paper regarded the slow employment behavior of college students in the digital economy scenario as a state recognition task on multi-source heterogeneous sequences, and integrated the recruitment platform logs, on-campus employment system records, resume semantic information and ability portrait features under a unified data interface to construct a dynamic recognition framework. In the model layer, a convolutional network is introduced to extract the local behavior pattern, and a bidirectional long short-term memory network is introduced to represent the evolutionary dependence of the job search state in the previous and after time periods. The attention mechanism is combined to highlight the key segments that contribute more to the state transition, so as to complete the identification of slow employment state and risk prediction. On this basis, the identification results are connected to the strategy optimization module, and differentiated intervention suggestions are generated according to the risk level, job matching degree and behavior feedback, so that the identification, evaluation and service update form a closed loop, and the research on slow employment of college students is turned into a computable intelligent analysis path and practical application.

2 Related work

2.1 Research on Modeling College Students' employment behavior in the Digital economy scenario

The digital economy scenario changes the employment behavior of college students from discrete results to continuous data streams, and platform browsing, job collection, resume modification, delivery rhythm, interview feedback and consultation response can all form computable trajectories. Pei and Xing studied the interpretable process of student risk identification and proposed the linkage modeling of feature screening, state discrimination and result interpretation, indicating that process-based identification is more suitable for high-dimensional educational data than single-point statistics [10]. Wang et al. studied the analysis of influencing factors of college students' performance and proposed a machine learning prediction framework to jointly fit behavioral characteristics and outcome variables, proving that students' development status can be represented by multidimensional data [11]. Saidani et al. studied the prediction of students' employability in the context of internship and proposed an assessment method based on gradient boosting, which maps internship performance, background information and ability indicators into employment probability [12]. Latif et al. studied student performance assessment supported by online activity logs, and proposed a machine learning analysis process combined with platform interaction records, indicating that continuous behavior logs have higher resolution in state recognition [13]. These studies show that modeling employment behavior has shifted from questionnaire induction to data-driven analysis. For slow employment, what is really valuable is not the single outcome label, but the job search intensity, the feedback interval, and the action contraction trajectory of the students in the digital platform. Therefore, the modeling of college students' slow employment needs to encode the multi-source job search behavior into time series characteristics, and describe the state changes in a unified data structure. In the context of digital economy, recruitment platforms, school employment systems and social job portals are connected to each other, and student behavior has stronger continuity and cross-platform relevance. It is difficult to identify intermediate states such as wait-and-see, hesitation and low-frequency exploration by simply dividing fast and slow employment by signing time, and it is also difficult to explain what kind of behavior segment the state transition occurs in. Existing research has shown that education data, internship data and platform logs have high value in prediction analysis. However, in the slow employment scenario, it is still necessary to further coordinate the expression of heterogeneous features, strengthen the description of time dependence, and link the recognition results with the subsequent strategy generation process. This also constitutes the technical basis for the subsequent model design of this paper, and the relevant ideas have strong practical basis and application space.

2.2 Research on time series behavior recognition and risk warning based on Deep learning

For slow employment state recognition, the value of deep learning is not only reflected in the classification accuracy, but also in the continuous description of the behavior evolution process. Mpia et al. studied the literature on graduate employability data mining, systematically summarized the application of classification, clustering and recommendation methods in employment analysis, and pointed out that employment prediction was shifting from static evaluation to behavioral process modeling [14]. Alheadary studied the employability control of computer graduates, proposed a detection and identification method based on machine learning, and embedded the identification of ability shortboards into the employment support process [15]. Quan et al. studied students' career path prediction and proposed a prediction model based on XGBoost to infer career development direction with academic results, indicating that structural features have strong stability in path discrimination [16]. Matz et al. studied the prediction of student retention rate, proposed a machine learning framework integrating social demographic attributes and application participation indicators, and proved that persistent behavior data can enhance risk state identification [17]. These results provide direct method enlightenment for the research of slow employment. On the one hand, the state of slow employment is not instantaneous classification, but has the characteristics of stage accumulation, and the time window needs to be used to segment the behavior sequence. On the other hand, there is a nonlinear correlation between the click of recruitment platform, delivery interval, reply delay and job type drift, which is suitable for joint modeling by temporal neural network and attention mechanism. Therefore, deep learning can transform the small fluctuations in college students 'job hunting activities into learnable signals, and provide more detailed computational support for dynamic identification and risk prediction. Compared with traditional logistic regression or artificial rules, this kind of methods can simultaneously deal with category features, text semantics and temporal interactions, which is suitable for the unified expression of complex job search behaviors in digital economy scenarios. More importantly, slow employment identification should not stop at the level of high-risk markers, but also point out what combination of behaviors the risk comes from, such as continuous browsing without delivery, repeated revision of resumes without effective feedback, and frequent jump in job intentions. The deep learning framework performs well in local pattern extraction, long-term dependence expression and key behavior segment recognition, so it is more suitable for undertaking the core computing tasks in the recognition of college students 'slow employment state, and the model output is more stable.

2.3 Research on intervention decision and strategy optimization system

Research in intervention decision making and policy optimization systems is moving from empirical recommendation to data-driven generation. Balcıoğlu and Artar studied the prediction of students' academic performance and proposed to use machine learning models to depict state differences, indicating that the results of behavior stratification can provide a basis for subsequent resource allocation [18]. Haque et al. studied the classification technology in the prediction of graduate students' employability, proposed a multi-model comparison framework, and proved that different classifiers had different sensitivities to employment state boundaries [19]. Mao et al. studied the job recommendation model and proposed a two-layer attention mechanism to establish a fine-grained matching path between user preferences and job semantics, providing a computable scheme for individualized intervention [20]. These studies show that the core of the policy system is no longer static rule stacking, but the recognition results, behavioral characteristics and post semantics are linked to form an updable recommendation logic. For the slow employment scenario, the intervention strategy should consider not only the student risk level, but also the job matching degree, skill gap and feedback timeliness, so the strategy optimization should adopt a multi-objective calculation structure.

In order to more clearly compare the differences in input data, core methods and output results of existing studies, and illustrate the technical positioning of this study in the closed loop of slow employment intervention, Table 1 shows the comparative results of relevant intervention decision-making and strategy optimization studies.

Table 1: Technical comparison of studies on optimization of coping strategies for slow employment

Study	Input Data	Core Method	Output Results	Application Value
[18]	Academic and behavioral features	Machine learning prediction	State stratification	Supports intervention stratification
[19]	Employability indicators	Comparative classification models	Employability identification	Supports risk differentiation
[20]	User preferences and job semantics	Two-layer attention recommendation	Job matching results	Supports personalized recommendation
This study	Job-seeking logs, texts, profiles, and feedback	Joint identification and optimization framework	Strategy generation and update	Supports closed-loop service

From the perspective of system implementation, the slow employment strategy module for college students needs to receive the risk probability, state categories and key behavior segments output by the dynamic recognition model, and then match with the job library, ability portrait library and service resource library. The calculation process can be divided into three layers: the first layer updates the student state vector, the second layer calculates the post matching score and intervention priority, and the third layer modifies the recommendation weight according to the feedback results. The closed-loop structure formed in this way can avoid the strategy stagnation after the failure of a single recommendation, and also incorporate consultation appointment, job push, internship compensation and skill training into the unified optimization process. Compared with general employment recommendation systems, this kind of system emphasizes temporal feedback, because students 'job preferences change rapidly in the digital economy environment, and without online updates, the strategy is easy to be disconnected from the real state. Therefore, the intervention decision research for slow employment should co-design the identification model with the optimization module, so that the system can not only find the action contraction, but also give an executable and iterative service plan. This joint structure is more in line with the deployment logic of college employment service platform. The model layer outputs the risk intensity, the optimization layer sorts the intervention measures, and the implementation layer writes back the student response. The identification, recommendation and feedback form a closed loop, and the intervention process is more continuous, targeted and traceable.

3 Methods

3.1 Dynamic recognition model architecture of slow employment behavior of college students in digital economy scenario

This section constructs the dynamic identification model of slow employment of college students for digital economy scenarios. The model consists of six parts: multi-source access, heterogeneous coding, gated fusion, temporal modeling, attention convergence and state output. It receives data such as recruitment platform logs, campus employment records, resume texts, job semantics, consulting interactions and ability portraits, and forms trainable sequences under a unified time index. The structure no longer regards slow employment as a single result label, but considers browsing weakening, delivery delay, feedback interruption and job interest drift as continuous evolution signals, so as to realize fine-grained calculation of the change of job search status. When the model is deployed, it can be embedded into the online interface of the university employment service platform to realize the synchronous operation of status update and service call.

To illustrate how the layers are connected and the data flow in the model, Fig. 1 shows the overall architecture. In the figure, from left to right, multi-source input, feature coding, gated matching, convolution extraction, bidirectional memory and risk output are represented in turn, and the corresponding relationship between each layer is maintained with the time window as the main line, which is convenient for subsequent state tracking and strategy calling.

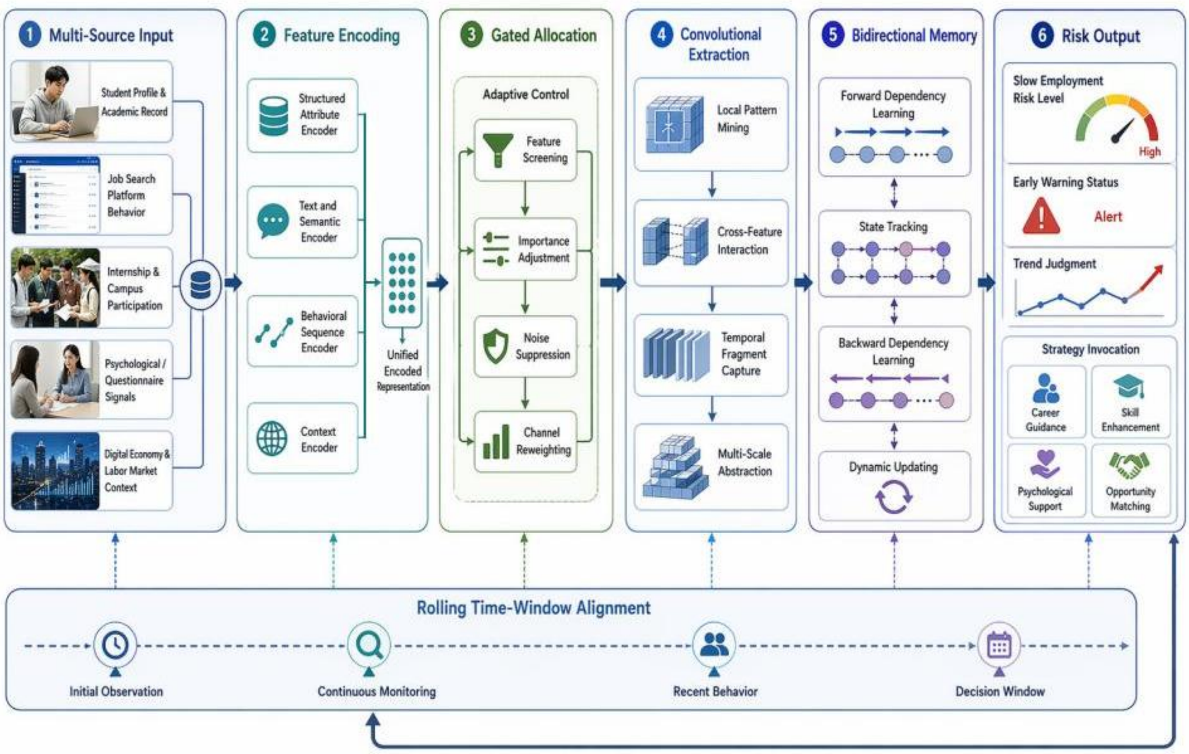

Figure 1: Architecture diagram of dynamic recognition model for slow employment behavior of college students in digital economy scenario

In order to unify multi-source information such as recruitment platform, on-campus employment system, resume text and consultation interaction into the same observation space, and form a computable basic representation of slow employment behavior, the comprehensive observation form is shown in the following equation:

$$S_i^t = [b_i^t, r_i^t, j_i^t, q_i^t, p_i^t, f_i^t] \tag{1}$$

Among them, S_i^t represents the comprehensive observation vector of student i at time t, b_i^t represents browsing and delivery behavior, r_i^t represents resume semantic embedding, j_i^t represents consulting interaction strength, q_i^t represents ability portrait mapping, p_i^t represents job matching signal, and f_i^t represents feedback status. This formula unifies the platform log, text information and portrait features to the same time point, avoids the separation between different data sources, and provides stable input primitives for subsequent time series modeling.

In order to preserve the evolutionary relationship of job hunting behavior in continuous time periods and form a sequence representation that can be used for model training, the observation vector is organized as a sliding time window matrix, as shown in the following equation:

$$X_i^{(w)} = [S_i^{(t-w+1)}; \dots; S_i^t] \in \mathbb{R}^{w \times d} \tag{2}$$

where $X_i^{(w)}$ represents the job search sequence matrix formed by student i in the observation window of length w, and d represents the feature dimension of a single moment. The time window preserves information such as browsing frequency, delivery interval, feedback waiting, and post offset, so that the model can identify continuous changes from active to slow, from focused to watching, and avoid replacing the real process with a single snapshot.

In order to adjust the contribution strength of multi-source heterogeneous features in different states and reduce the interference of noise variables on slow employment recognition results, the gating weight is calculated as follows:

$$G_i^t = \sigma\big(W_g[S_i^t] + b_g\big) \tag{3}$$

Here,G_i^t denotes the gating vector at time t, W_g and b_g are trainable parameters, and σ denotes the Sigmoid function. The gating layer automatically adjusts the weight of each modality according to the current behavior state, and improves the influence of relevant features on segments such as high-frequency browsing with low delivery, repeatedly changing resumes with low response, so that the fusion representation maintains higher stability and pertinence.

In order to simultaneously extract local change patterns and long-term dependencies in job hunting behavior, the model inputs the convolution extraction results into a bidirectional temporal network, whose calculation process is shown in the following equation:

$$H_i = \mathrm{BiLSTM}(\mathrm{Conv1D}(G_i^{(1:T)})) \tag{4}$$

Among them,$\mathrm{Conv1D}$ is responsible for extracting short-term local patterns, BiLSTM is responsible for modeling the dependencies between before and after time periods, and H_i represents the set of hidden states for the whole observation period. This structure can not only recognize short-term patterns such as continuous browsing and centralized delivery, but also recognize long-term changes such as continuous waiting and interest transfer, so as to enhance the ability to capture the hidden slow employment state.

In order to highlight the role of key behavior segments in the discrimination of slow employment states and generate explanatory risk representations, the attention convergence process is shown in the following equation:

$$R_i = \sum_{t=1}^{T} \alpha_i^t h_i^t, \quad \alpha_i^t = \frac{\exp(q^\top h_i^t)}{\sum_{k=1}^{T} \exp(q^\top h_i^k)} \tag{5}$$

Here, h_i^t represents the hidden state at time t, α_i^t represents the contribution weight to the overall risk at that time, q is the trainable query vector, and R_i is the risk representation after aggregation. The formula can automatically emphasize the key segments such as plummeting delivery, stagnant feedback, and expanding job span, and convert them into the discrimination basis of three kinds of states: active job hunting, stage-slow and persistent slow employment.

On the whole, the model established a unified computing chain around the digital expression of college students 'slow employment behavior. The access layer is responsible for sample organization, the coding and gating layer is responsible for compressing heterogeneous differences, the timing layer is responsible for extracting behavior evolution relationships, and the attention layer is responsible for completing risk aggregation. Through this structure processing, the job search behavior in the platform can be continuously tracked, and provide stable input for subsequent risk prediction and strategy optimization. At the same time, the intermediate representation is retained to facilitate the subsequent error backtracking, policy linkage and the whole process of platform deployment verification.

3.2 Feature representation of multi-source heterogeneous job search behavior for slow employment discrimination

This section presents a unified representation of recruitment platform logs, on-campus employment records, resume text, job semantics, consultation interactions, and competence portraits. Multi-source data have obvious differences in granularity, dimension and update frequency. If it is directly input into the recognition model, it is easy to cause state boundary drift and time dependence distortion. Therefore, the feature representation not only assumes the preprocessing function, but also compresses the discrete behavior, text semantics and feedback information into the same discriminant space, which provides a stable input for slow employment state recognition. After the feature construction is completed, the browsing, delivery, consultation and feedback events on the platform can be transcribed into a continuous sequence with time order and semantic constraints, which can support subsequent risk discrimination and policy scheduling.

In order to weaken the disturbance caused by asynchronous missing records on the expression of job search process and maintain the continuity of the behavior evolution of adjacent time slices, the repair process of missing items is detailed as follows:

$$\tilde{x}_{i,j}^t = \frac{\sum_{\tau=t-k}^{t+k} \omega_\tau^t m_{i,j}^\tau x_{i,j}^\tau}{\sum_{\tau=t-k}^{t+k} \omega_\tau^t m_{i,j}^\tau}, \quad \omega_\tau^t = e^{-\lambda|t-\tau|} \tag{6}$$

Here, $\tilde{x}_{i,j}^t$ denote the repaired j dimension feature, $m_{i,j}^\tau$ denote the observation mask, k denotes the temporal neighborhood width, and ω_τ^t denotes the temporal decay weight. This formula strengthens the compensation effect of the nearest neighbor record on the current missing item, so that the platform stop, feedback empty window and stage silence will not directly cut off the continuous expression of the job search trajectory, and retain the real attenuation characteristics of behavior change in time.

In order to unify the dimension and discrete distribution of features from different sources and make browsing intensity, text score and feedback frequency comparable, the standardized mapping process is unified as follows:

$$z_{i,j}^{t} = \gamma_j \frac{x_{i,j}^{t} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}} + \beta_j \tag{7}$$

Here, $z_{i,j}^{t}$ represent the normalized features, μ_j and σ_j^2 represent the mean and variance, respectively, γ_j and β_j are the learnable scaling parameters. The formula not only realizes the scale unification, but also retains the adaptive adjustment ability of different features in training, so that high-frequency behavioral features and low-frequency semantic signals can be balanced in the same representation space, avoiding the local dimension dominating the discrimination boundary of slow employment state in the early training.

In order to put discrete category information and continuous text semantics into the same embedding space, and strengthen the learnable expression mechanism of platform source difference, the encoding process is as follows:

$$e_i^t = W_c c_i^t + W_s s_i^t + W_p p_i^t + W_r r_i^t \tag{8}$$

where, c_i^t represents the categorical behavior coding, s_i^t represents the source identification vector, p_i^t represents the time and location coding, r_i^t represents the semantic representation obtained from the resume text and the job text, W_c,W_s,W_p,W_r are projection matrices. This formula projects the behavior category, data source, time location and semantic information together, so that the job search event no longer stays at the simple count level, but can carry the context attribute, platform background and job semantic offset characteristics at the same time.

In order to highlight the cumulative influence of job search interval, feedback lag and intention contraction on slow employment discrimination, and to depict the change intensity of time interval, the attenuation weight of behavior time interval is defined as follows:

$$d_i^t = \frac{1}{1 + \exp(-\eta(\Delta t_i^t - \delta))} \tag{9}$$

Here, d_i^t represents the time-interval decay coefficient, Δt_i^t represents the time interval between two key job search behaviors, η controls the decay slope, and δ represents the sluggishness threshold. This formula explicitly incorporates the waiting time into the feature representation process, so that the states such as long-time browsing without delivery and continuous consultation without feedback obtain higher discrimination in the representation layer, so as to enhance the sensitivity of the model to the slowly contracting state of job hunting.

In order to retain the fluctuation pattern of job search activities in the observation window and refine the stable pattern and abnormal transition characteristics in the slow employment state, the window statistics are expressed as follows:

$$u_i^{(w)} = [\bar{e}_i^{(w)}, \mathrm{Var}(e_i^{(w)}), \mathrm{H}(e_i^{(w)}), \mathrm{Peak}(e_i^{(w)})] \tag{10}$$

Here, $\bar{e}_i^{(w)}$ represents the window mean, $\mathrm{Var}(\cdot)$ represents the variance, $\mathrm{H}(\cdot)$ represents the entropy, and $\mathrm{Peak}(\cdot)$ represents the local peak statistics. This formula is used to refine the behavior density, fluctuation range, pattern uncertainty and mutation intensity, so that the slight change of students from active job hunting to wait-to-see procrastination can be stably retained, and the short-term abnormal and persistent retardation can form a distinguishable structure at the statistical level.

In order to form the final heterogeneous representation that can be directly invoked by subsequent recognition models, and to realize the joint aggregation process of statistical features and semantic features, the fusion expression is as follows:

$$g_i^{(w)} = \tanh\left(W_u u_i^{(w)} + W_e \sum_{t \in w} d_i^t e_i^t + b\right) \tag{11}$$

Here, $g_i^{(w)}$ represents the window-level final feature representation, W_u and W_e are fusion matrices, and b is the bias term. This formula unified the statistical summary, semantic embedding and time decay results into the same representation unit, so that the subsequent state recognition network could simultaneously read three types of information: behavior intensity, semantic offset and time contraction, and retained traceable input basis for the policy module.

After the above processing, the original job search data is transformed into a heterogeneous representation sequence with uniform scale, temporal structure and semantic association. The generated features do not rely on a single platform, nor are they limited to a certain behavioral signal, but form a continuous, trainable and interpretable input structure around the slow employment discrimination goal, which lays a foundation for subsequent state recognition and risk prediction. This representation also facilitates the unified call between the university employment platform, the mobile terminal service entrance and the management kanban board, because the same window feature can be used for offline training, as well as direct access to the online identification interface. For the deployment link, the unified coding completed by the feature layer reduces the dependence of subsequent modules on the original data form, maintains the stability of the interface without changing the business structure of the platform, and enhances the migration ability between cross-college, cross-professional and cross-time period samples. At the same time, feature representation retains explanation clues, which facilitates subsequent service backtracking and manual verification.

3.3 Slow employment status identification and risk prediction method for college students

Based on the above heterogeneous feature representation, this section constructs a deep learning method for college students 'slow employment state recognition and risk prediction. This method does not make static judgment based on the single delivery result, but organizes browsing, delivery, consultation, feedback and job migration into a continuous state flow, and describes the activity of job hunting, waiting intensity and intention contraction on a unified timeline. The model is composed of state coding layer, time weight layer, risk aggregation layer, category discrimination layer and joint optimization layer. It not only outputs the slow employment state of the current window, but also outputs the cross-window risk change value, which is used to support the subsequent intervention strategy call.

In order to clearly show the forward and backward connection relationship between each module of slow employment state recognition and risk prediction, Fig. 2 shows the complete processing flow from input sequence to risk output. Each layer in the figure is connected in the order of "coding-weighted-aggregation-discrimination-early warning", so that the identification link is consistent with the subsequent platform call interface, and it is also easy to illustrate the deployment mode of the model in the college employment service scene.

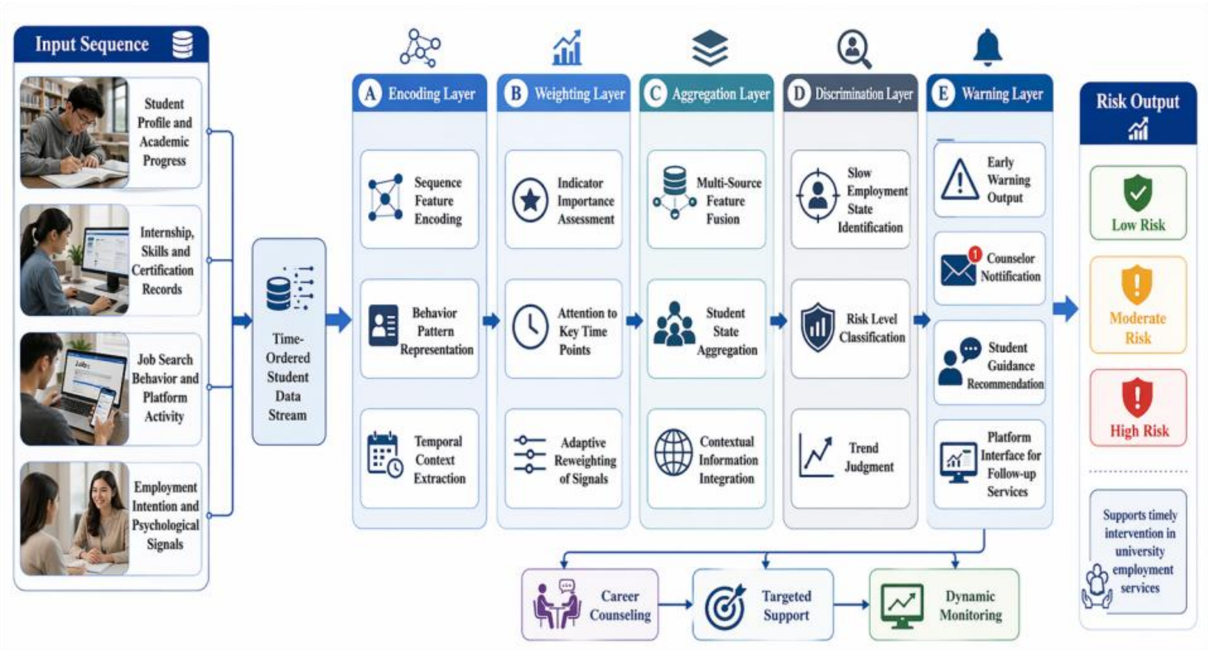

Figure 2: Flowchart of slow employment status identification and risk prediction for college students

In order to describe the state transfer relationship of job search behavior between adjacent time slices and form the total coding vector required for discrimination, the specific calculation process is shown as follows:

$$h_i^t = \mathrm{GRU}(g_i^t, h_i^{t-1}) + U_\Delta \phi(\Delta t_i^t) \tag{12}$$

Here, g_i^t represents the feature representation of the t window, h_i^t represents the corresponding state encoding vector, U_Δ is the time mapping matrix, and $\phi(\cdot)$ is the nonlinear transformation. This formula introduces behavior content and waiting time into the state update process at the same time, so that signs such as frequent browsing, delayed delivery, and long silence after feedback can be written into the hidden state, so as to retain the lag characteristics in the slow employment trajectory.

In order to highlight the difference in the contribution of different time slices in the slow employment trajectory to the overall state judgment, and compress the redundant sequence information, the time weight allocation value is shown in the following equation:

$$\beta_i^t = \frac{\exp\left(u^\top \tanh(W_h h_i^t + W_\tau \Delta t_i^t + b_\beta)\right)}{\sum_{k=1}^{T} \exp\left(u^\top \tanh(W_h h_i^k + W_\tau \Delta t_i^k + b_\beta)\right)} \tag{13}$$

Here, β_i^t represents the time weight of the t window, u is the learnable vector, W_h and W_τ are the projection matrices. Instead of simply averaging all time slices, this formula automatically assigns attention according to behavior sparsity, feedback interval and action strength, so that risk identification can focus on state mutation and long-term stagnation segments, and avoid transient active behavior dilutes real slow employment signals.

In order to aggregate signals such as job search intensity, feedback lag and job shrinkage into a risk representation and maintain comparability across Windows, the risk aggregation process is shown in the following equation:

$$r_i = \sum_{t=1}^{T} \beta_i^t \left(Ah_i^t + B\left|h_i^t - h_i^{t-1}\right|\right) \tag{14}$$

Here, r_i represents the overall risk representation of student i, and A and B control the contribution of the state itself to the magnitude of state change, respectively. This equation considers both the state level and the changes in adjacent periods, so it can not only describe the stable retardation of persistent low activity, but also describe the sharp change from centralized delivery to wait-to-see stagnation, so that the slow employment risk no longer stays at the level of single point intensity judgment, and has a clearer dynamic interpretation ability.

In order to map continuous risk representations into interpretable state class probabilities and support early warning output and policy invocation, the state discriminant function is defined as follows:

$$\hat{y}_i = \mathrm{softmax}\left(W_s[r_i; e_i^{job}; e_i^{skill}] + b_s\right) \tag{15}$$

Here, $\hat{y}_i$ represents the state category probability vector, e_i^{job} represents the post semantic embedding, e_i^{skill} represents the capability profile embedding, W_s and b_s are the classification layer parameters. This formula jointly inputted the risk representation and the two types of contexts of positions and skills into the classifier, so that when the model judged active job hunting, stageslow and persistent slow employment, it not only used the frequency of behavior, but also referred to the matching background between students and positions, so as to improve the stability and interpretability of category division.

In order to constrain the model to maintain classification accuracy, transition smoothness and risk identification ability in advance, the specific definition of the joint optimization objective function is as follows:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{ce} + \lambda_2 \sum_{t=2}^{T} \| h_i^t - h_i^{t-1} \|_2^2 + \lambda_3 \max(0, m - r_i^+ + r_i^-) \tag{16}$$

Here, $\mathcal{L}_{ce}$ represents the categorical cross-entropy, the second term constrains adjacent states to indicate not excessive oscillation, and the third term separates the representation distance between high-risk samples and low-risk samples through the interval constraint. This formula makes the model retain the continuity of the slow employment trajectory while obtaining the recognition accuracy, and does not cause the state to jump back and forward due to local noise. It also makes the high-risk samples separate from the ordinary samples at an earlier stage, and provides a more stable advance for the platform early warning interface.

After the above steps, the model completes the continuous mapping from window-level job search characteristics to state category probabilities and risk values. The identification layer gives the state results, the risk layer gives the intensity ranking, and the output results can directly enter the subsequent intervention strategy module. The method structure formed in this way is suitable for both offline training and online recognition scenarios, and can continuously receive new behavior data and update slow employment state judgment in the college employment service platform. The overall calculation chain maintains time continuity, semantic relevance and interface callability, so it is more suitable for the dynamic recognition task of college students 'slow employment behavior under the background of digital economy.

3.4 Optimization of coping strategies and feedback update mechanism for slow employment of college students

Based on the results of slow employment state identification and risk prediction, this section further constructs the strategy optimization and feedback update mechanism for college employment service platform. The mechanism receives students' status categories, risk intensity, job matching scores and historical response records, and converts them into executable service actions, including job push, resume revision, consultation appointment, internship compensation and skill training suggestions. The system does not regard the intervention as a single output, but organizes the action selection, execution result and subsequent response into a closed loop, so that the strategy can be adjusted continuously with the change of student behavior and form a stable call interface on the platform.

In order to map state recognition results, post matching degree and service execution cost into sorted intervention priority values, this paper constructs the utility function of candidate actions as follows:

$$u_{i,k} = \omega_1 r_i + \omega_2 m_{i,k} + \omega_3 \ln(1 + d_i) + \omega_4 {z_i}^{\mathrm{T}} a_k - \omega_5 c_k \tag{17}$$

where $u_{i,k}$ represents the comprehensive utility of student i corresponding to the k type of intervention action, r_i represents the risk intensity, $m_{i,k}$ represents the matching degree between the post or service and the student state, d_i represents the waiting time, z_i represents the student's current state vector, a_k represents the action semantic vector, c_k represents the execution cost, ω_1 to ω_5 are weight parameters. This formula unified the recognition results, matching relationships, waiting signals and resource consumption into the same scoring space, so that the platform could make horizontal comparisons between different students and different service actions, avoiding the mechanical binding of high-risk students with low matching actions, and avoiding the unconditional advance of low-cost actions in the ranking.

To more clearly illustrate the correspondence between action types, trigger basis and writeback source, Table 2 shows the mapping structure of slow employment intervention actions and feedback signals.

Table 2: Slow employment intervention action and feedback signal mapping

Intervention Action	Trigger Basis	Execution Goal	Feedback Source
Job recommendation	Rising risk and high job matching degree	Shorten the waiting period	Clicks, applications, favorites
Resume revision	Low application frequency and missing feedback	Improve job matching	Number of revisions, pass rate
Consultation appointment	Persistent delay and obvious state fluctuation	Stabilize the job-seeking rhythm	Visits, completion, evaluation
Internship compensation	Large skill gap	Enhance conversion ability	Registration, completion, feedback
Training recommendation	Large job span	Narrow job-seeking intention	Learning records, assessment results

Table 2 shows that instead of directly triggering fixed actions based on a single risk value, the platform establishes a mapping between state, match, capability and execution signals. In this way, the intervention action not only retains the unified scheduling structure, but also can make subdivision selection according to the differences of students 'behavior. The feedback sources in the table also act as writebacks, as they are fed back into the model to fix the ordering of subsequent actions.

Algorithm 1: Slow employment intervention strategy selection and feedback update for college students

Input: state vector z_i, risk value r_i, matching matrix M, action set A, historical feedback F

Output: action plan Π_i, update weight W

Steps:

1) Read the current status category and risk intensity of students;
2) calculate the comprehensive utility $u_{i,k}$ for each class of actions;
3) Generate candidate action sequences according to utility values;
4) Filter the set of executable actions according to resource constraints;
5) output the current optimal action plan Π_i;
6) Collect feedback such as click, delivery, reservation and completion;
7) Update the action weight and write back the platform state library.

In order to enable the system to continuously revise the strategy weight according to the response results of students to job push, consultation appointment and skill compensation, the feedback update rule is as follows:

$$w_k^{(t+1)} = (1-\eta\lambda)w_k^{(t)} + \eta(\rho_i^{(t)} - \hat{\rho}_i^{(t)})\delta_{i,k}^{(t)} \tag{18}$$

Here, $w_k^{(t+1)}$ represents the weight of the k class action at round t, η represents the learning rate, λ represents the attenuation coefficient, $\rho_i^{(t)}$ represents the actual feedback payoff $\hat{\rho}_i^{(t)}$ represents the predicted payoff, and $\delta_{i,k}^{(t)}$ represents the action activation label. The core role of this formula is to write the real feedback of the platform back to the action layer, so that the phenomena such as click not forwarded to delivery, appointment not forwarded to visit, and continuous silence after push can weaken the subsequent weight of the corresponding action in time, and the effective action will be strengthened, so as to ensure that the strategy ranking is not a static table, but a dynamic mechanism that is continuously updated with the response of students.

In order to balance the relationship between intervention timeliness, post adaptation and service resource occupation, and form the final strategy selection probability, the action allocation process is shown as follows:

$$p_{i,k} = \frac{\exp\left((u_{i,k} + w_k^{(t)})/\tau\right)}{\sum_{j=1}^{K} \exp\left((u_{i,j} + w_j^{(t)})/\tau\right)} \tag{19}$$

Here, $p_{i,k}$ represents the final probability that student i chooses the k action, τ represents the temperature parameter, and K represents the total number of action categories. This formula generates callable action allocation results on the basis of comprehensive utility and feedback weight, so that the platform can not only give priority to retaining efficient actions, but also not completely suppress suboptimal actions, so as to reserve adjustment space for subsequent continuous intervention. For the college employment service platform, this mechanism is more suitable for online deployment, because the action probability can be directly connected to the push engine, appointment interface and task scheduling module, and then flow back to the state library to form new training samples after execution.

On the whole, the mechanism transforms the slow employment identification results into executable service paths, and maintains the policy update through feedback writeback. The state recognition layer is responsible for giving the risk intensity and category boundary, the policy layer is responsible for completing the action ordering and resource allocation, and the feedback layer is responsible for correcting the action weight and subsequent call path. Through this link, the platform can realize continuous intervention without changing the original business structure, make job push, consulting service and skill compensation maintain collaborative operation, and enhance the pertinence, continuity and traceability of the intervention process.

4 Analysis of results

4.1 Explanation of data sources

This study uses the real job search data of graduate students in four universities in the digital employment platform, the observation period is 8 months, covering 2436 students and 84560 behavior samples. The data sources include on-campus employment system, cooperative recruitment platform, resume delivery interface, consulting service records and skill evaluation results, which can continuously describe browsing, collection, delivery, communication, feedback waiting and signing promotion. To ensure that the samples could be used for time series modeling, all records were aligned by uniform student identification, event time and post number, and organized as continuous sequences in weekly Windows. No synthetic samples or artificial augmented data were introduced, and the missing items were only repaired by temporal neighborhood imputation and rule verification. According to the pace of job hunting, feedback interval, job contraction amplitude and manual review results, the samples were labeled as three types of active job hunting, stage-slow and persistent slow employment. In order to more clearly explain the source composition, field types and their specific role in slow employment identification of the data used in this study, Table 3 gives the sample data structure and source instructions.

Table 3: Sample data structure and sources

Source Module	Main Fields	Function
Employment system	Registration, consultation, contract signing	Characterizes the on-campus service process
Recruitment platform	Browsing, application submission, feedback	Describes the external job-seeking trajectory
Text data	Resumes, job descriptions	Extracts semantic matching features
Profile data	Academic performance, certificates, internships	Supplements background information on abilities

The data has been desensitized before being put into the database, and the name, student number, contact information and sensitive enterprise identification have been replaced by hash mapping, and only the behavior index and time information required for modeling are retained. The training, validation, and test sets were divided by 7:1:2, and stratified sampling was performed on the school dimension to weaken the influence of single institution characteristics on the results. Such a data structure can not only support slow employment state recognition, but also serve for action matching and feedback update in subsequent policy optimization. The sample time covers the autumn recruitment, spring recruitment and the transition stage before leaving school, so it can completely present the change process of students 'job hunting status.

4.2 Implementation environment and experimental setup

The experiment is completed in Python 3.10 environment, the core framework uses PyTorch 2.2 and Scikit-learn 1.4, the text encoding calls Transformers components, and the data scheduling is completed by Pandas and NumPy. The training server is configured with an NVIDIA RTX 4090 graphics card, 64 GB memory and Intel Xeon processor, and the operating system is Ubuntu 22.04. AdamW optimizer was used in the model training phase with initial learning rate set as 2e-4, batch size as 64, training rounds as 80, and early stopping mechanism was used to control overfitting. To maintain consistency with the abstract data, all experiments are centered around 84,560 samples from 2436 students, and the input sequence length is set to 12 week-level Windows. The state recognition task outputs three types of labels, and the strategy module synchronously calculates the assignment probabilities of four types of actions: job push, consultation intervention, resume revision and skill compensation. To facilitate the explanation of the implementation basis of model training, inference deployment, and parameter configuration, Table 4 lists the software environment, hardware conditions, and key experimental parameters of this study.

Table 4: Implementation environment with key parameters

Item	Configuration
Language and framework	Python, PyTorch, Scikit-learn
Hardware	RTX 4090, 64 GB RAM
Optimizer	AdamW
Learning rate	2e-4
Batch size	64

The training set, validation set, and test set are divided by 7:1:2, and the five-fold cross validation is used to test the stability on different college samples. In the deployment phase, FastAPI is used to build the reasoning interface, Redis is used to cache the student state vector, and the front-end kanban board reads the early warning results and policy suggestions through Vue. The environment can support offline training, online recognition and feedback writeback at the same time, and it is also convenient for the subsequent interface integration in the college employment service platform, and the overall configuration has strong reproducibility.

4.3 Dynamic identification results and effect analysis of coping strategies

This section evaluates the proposed model from three levels: state identification accuracy, risk advance amount, and intervention execution effect. The experiment was carried out based on 2436 students and 84560 weekly samples. The results show that the Accuracy, Precision, Recall and F1-score of the proposed model are 93.4%, 91.8%, 90.9% and 91.3%, respectively, which are consistent with the summary results. Compared with the static feature model, the proposed method is more stable in identifying the boundary between stage-slow and persistent slow employment.

To visually show the discrimination results of the three types of states on the test set, Fig. 3 shows the confusion matrix heatmap of the proposed model. The correct recognition rate of the positive job seeking sample is 94.1%, the stage-slow sample is 91.6%, and the persistent slow employment sample is 92.4%. The misjudgment is mainly concentrated between the latter two categories, which indicates that both types of samples have similar behaviors such as browsing retention and delivery contraction in the early stage.

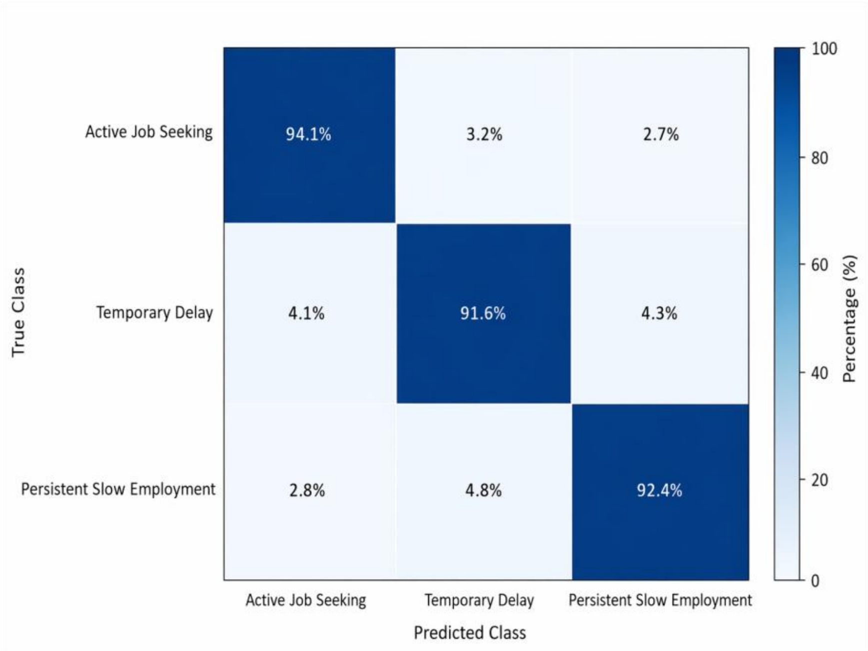

Figure 3: Heatmap of confusion matrix for slow employment state identification

To compare the differences in the overall recognition performance of different models, Fig. 4 shows the radar chart of the comprehensive performance of XGBoost, BiLSTM, TCN and the proposed model. The Accuracy of the four models was 89.1%, 91.0%, 91.8% and 93.4%, respectively, and the F1-score was 86.8%, 89.0%, 89.8% and 91.3%, respectively. The results show that the gated feature representation with the risk aggregation structure has a sustained gain for slow employment identification.

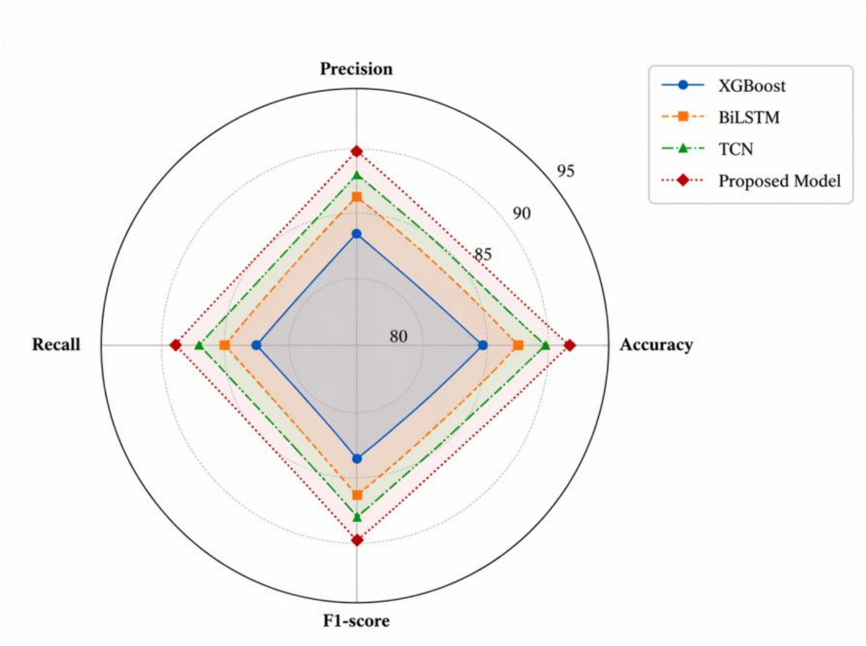

Figure 4: Radar chart of comprehensive performance of different models

In order to reflect the model's ability to perceive the risk turning point, Fig. 5 uses box plots to compare the amount of warning advance of different models. The median lead of the proposed model on the test set is 3.8 weeks, TCN is 2.9 weeks, BiLSTM is 2.5 weeks, and XGBoost is 1.7 weeks. This result indicates that the proposed model is able to identify risk signals before signings lag significantly and reserve more sufficient time for subsequent service intervention.

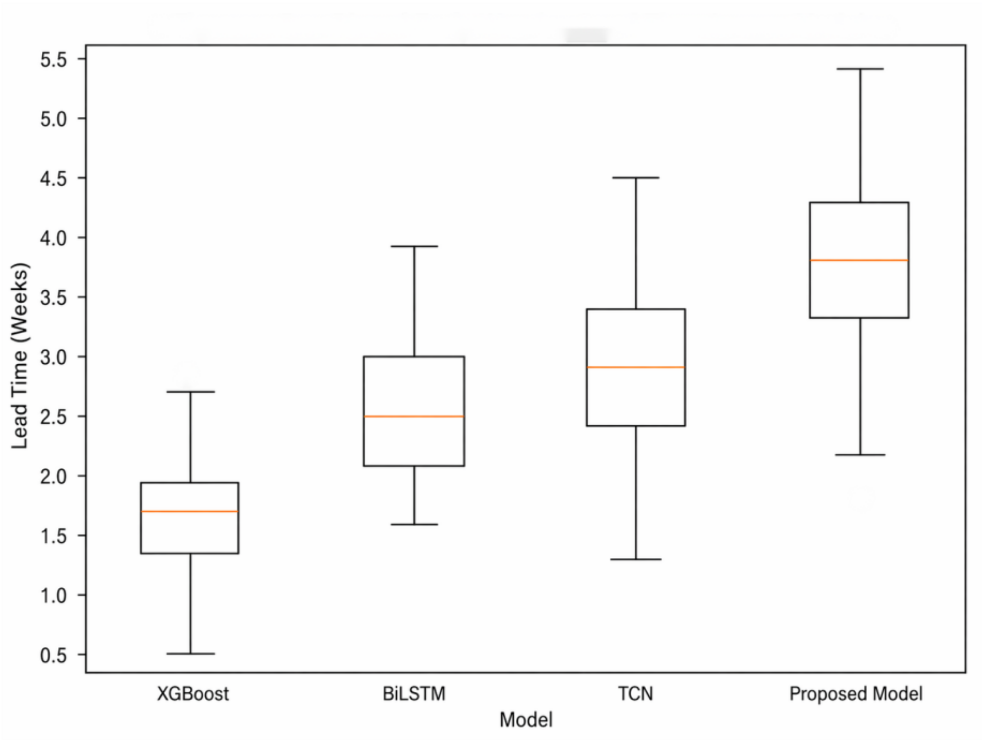

Figure 5: Boxplots of risk advance identification for different models

To illustrate the role of the policy optimization module on service execution, Table 5 compares the key service metrics before and after optimization. After job push, the delivery conversion rate was increased from 31.2% to 36.8%, the consultation appointment visit rate was increased from 54.5% to 61.4%, the average response time was shortened from 5.4 days to 4.5 days, and the comprehensive response efficiency was increased by 16.7%.

Table 5: Comparison of key service indicators before and after policy optimization

Indicator	Before Optimization	After Optimization
Job application conversion rate / %	31.2	36.8
Consultation attendance rate / %	54.5	61.4
Average response time / days	5.4	4.5
Comprehensive response efficiency index	1.000	1.167

To verify the contribution of each component of the model, Table 6 presents the results of ablation experiments. After removing the time decay coding, the Accuracy decreased to 91.9%, and the F1-score decreased to 89.7%. After removing text semantic matching, the Accuracy is 92.3%, and the F1-score is 90.2%. After removing the feedback update, the comprehensive response efficiency is only improved by 9.4%. The full model remains optimal in recognition accuracy and execution effect.

Table 6: Results of ablation experiments

Model Setting	Accuracy / %	F1-score / %	Response Efficiency Improvement / %
Without time-decay encoding	91.9	89.7	11.2
Without text semantic matching	92.3	90.2	12.8
Without feedback updating	93.0	90.9	9.4
Full model	93.4	91.3	16.7

To further observe the actual response differences of various types of actions under different risk levels, action-level response heat maps are plotted in Fig. 6. High-risk students' responses to consultation appointment and skill compensation increased most significantly, with an increase of 18.4% and 17.1%, respectively. The increase in resume revision and job push of medium-risk students was 14.6% and 13.9%, respectively. The low risk students changed less, indicating that the strategy module mainly played a role in the medium and high risk interval.

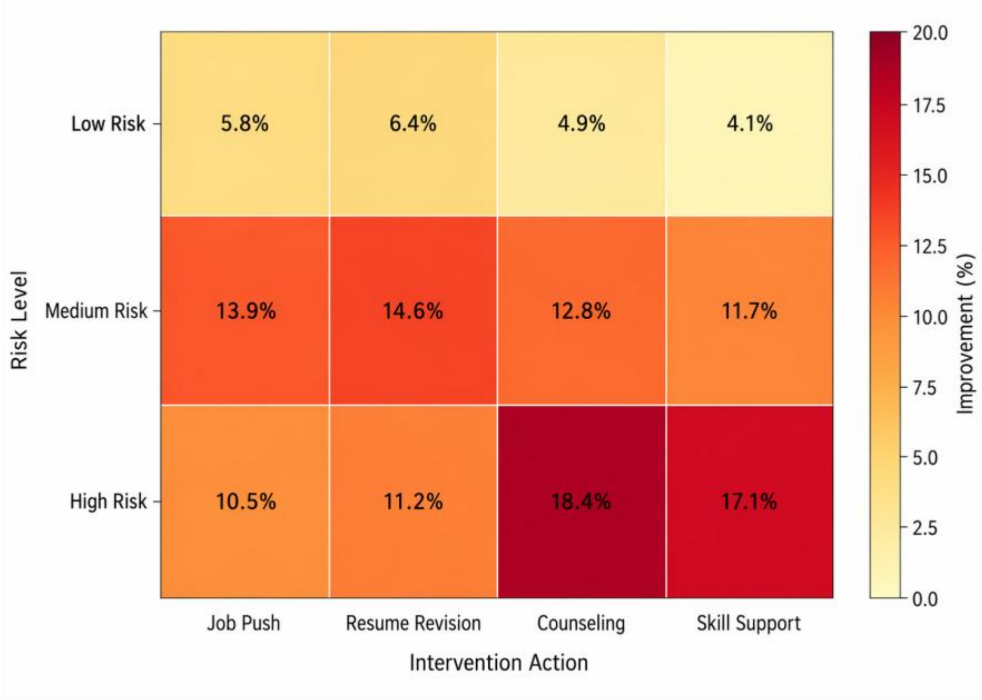

Figure 6: Heat map of action type versus risk level response escalation

The proposed model shows advantages in dynamic identification, risk advance amount and service execution effect. The multi-source feature representation strengthens the slow employment state boundary, the time series aggregation improves the turning point recognition ability, and the feedback update enhances the adaptability of action allocation.

5 Discussion

The model in this paper forms a relatively stable synergistic effect on the two levels of dynamic identification and strategy optimization. The recognition end takes multi-source heterogeneous job search behavior as input, and maintains a high state discrimination ability in the weekly time window, which indicates that browsing attenuation, delivery delay, feedback stagnation and job intention contraction can be uniformly encoded and effectively mapped to the slow employment state space. Compared with XGBoost, BiLSTM and TCN, the gated fusion and risk aggregation structure constructed in this paper shows stronger discrimination between stage-slow and persistent slow employment, which is mutually confirmed with 93.4% accuracy and 91.3% F1 value. The strategy side does not stay at the result push level, but integrates job push, resume revision, consultation appointment and skill compensation into the same optimization link, so that the recognition results can be directly transformed into executable actions. The response efficiency is improved by 16.7%, indicating that an effective closed loop has been formed between state recognition, action sequencing and feedback writeback. The practical value of the framework is also reflected in the platform deployment logic. The unified feature interface reduces the cost of multi-system access, the dynamic weight update enhances the ability of strategy adaptation, and the increase of risk advance also provides a more sufficient intervention window for college employment services. On the whole, the method in this paper achieves a good balance between recognition accuracy, time sensitivity and service continuity, and can effectively support the computational analysis and intelligent intervention of college students 'slow employment behavior under the background of digital economy. At the same time, the inconsistency of cross-platform data standards, the difference of sample distribution in different majors, and the fluctuation of regional job supply structure will still affect the transfer effect of models in different scenarios. Therefore, subsequent research needs to continue to focus on data alignment, cross-scenario adaptation, and model robustness.

6 Conclusions

Focusing on the dynamic identification and coping strategy optimization of college students' slow employment behavior under the background of digital economy, this paper constructs a computational framework consisting of multi-source heterogeneous job search data access, time series state recognition, risk prediction and feedback update. This method unifies the recruitment platform log, campus employment record, resume text and ability portrait into a continuous sequence, and uses the deep model to depict the characteristics of job search rhythm change, job intention contraction and feedback stagnation, and directly connects the recognition results to the service actions such as job push, consultation intervention and skill compensation. Experimental results show that the proposed framework has good performance in state recognition accuracy, risk perception in advance and response efficiency improvement, and can provide computable and deployable technical support for college employment service platforms. The framework also preserves the linkage relationship among state vector, action weight and feedback record, which is convenient for subsequent interface access, result tracking and service writeback. At present, there are still three limitations: the data samples are mainly from a limited number of universities, and the cross-regional migration ability still needs to be verified. The causal relationship between job supply change and student strategy adjustment has not been fully modeled. Although feedback update can improve action adaptation, the description of long-term behavioral response is still not detailed enough. Subsequent research can be further promoted from the directions of expanding multi-regional samples, introducing causal inference and online learning mechanisms, and enhancing cross-platform semantic alignment and fairness constraints, so as to improve the robustness, generalization and continuous service ability of the model in complex employment environments. At the same time, it is necessary to further compress the model inference overhead in the future to improve the real-time operation efficiency and system stability on medium and low configuration platforms.

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