ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

The Intelligent Development of College Student Behavior Management under the Background of Information Technology

Qian Wen[1,*]

[1] Normol University, Yichun Vocational Technical College, Yichun 336099, China

SUMMARY: *Under the background of campus informatization, this paper constructs an intelligent computing framework for college students 'behavior management. Relying on a university information system, this paper integrates learning platform logs, access control records, dormitory return information, class check-in sequences and campus network access segments to form a multi-source heterogeneous behavior dataset. Through unified time window reconstruction, cross-source semantic mapping and relationship enhancement modeling, the framework combines time convolution, graph attention and early warning decision mechanism to complete behavior recognition, state discrimination and risk stratification. The experimental results show that the behavior recognition accuracy of the proposed method on Camfield-Trace and LMS-Flow datasets reaches 0.931 and 0.918, respectively. The state discrimination accuracy on the synthetic dataset reaches 91.8%, the macro-average F1 value reaches 0.903, and the manual verification agreement rate reaches 93.5%. The average response delay is 84 ms, which indicates that the framework can still maintain a relatively stable output under the condition of complex heterogeneous events, and has the real-time processing ability under the condition of online operation.*

KEYWORDS: *Multi-source behavioral data; Graph attention network; Student behavior recognition; Intelligent early warning management*

1 Introduction

In recent years, the university governance platform, learning management system, access control system, dormitory management system and campus network log continue to converge, and students 'digital trajectories in teaching, life and transaction scenes show stronger continuity and computability. Building an intelligent behavior management mechanism around these data has become an important part of the construction of smart campus. Fahd et al. conducted a meta-analysis on the application of machine learning in academic performance, risk identification and dropout evaluation in colleges and universities, and pointed out that student behavior data had continuous predictive value [1]. Jang et al. proposed an interpretable machine learning early prediction framework to associate performance changes with behavior trajectories [2]. Flanagan et al. constructed an open evaluation early warning model based on reading behavior analysis, and proved that fine-grained process data can reflect participation status [3]. Susnjak et al. studied the role of learning analysis dashboard in the presentation of actionable information, providing technical reference for real-time feedback at the management end [4]. Ye and Pennisi used trajectory data to depict students' self-regulation activities, indicating that continuous behavior records are suitable for state modeling [5].

*JYwz082@163.com
https://doi.org/10.65102/is2026210 Published: 30 April, 2026

Trakunphutthirak and Lee proposed a progressive time series data mining method to predict academic performance [6]. Hellings and Haelermans verified the effect of learning analytics feedback on behavior and performance in programming courses [7]. Oqaidi et al. constructed a machine learning model for college student churn identification [8]. Pek et al. discussed the role of machine learning in identifying at-risk students and reducing failure rates [9]. Asthana et al. used regression machine learning model and learning coefficient to complete student performance prediction [10].

The existing results show that the digital analysis of student behavior has shifted from pure statistical description to multi-source fusion, time series modeling and intelligent decision-making. At the same time, campus behavior management is not limited to academic performance judgment, but also involves classroom attendance, work and rest rules, space access, platform interaction, abnormal aggregation and management response and other states. Only based on a single business system, it is easy to weaken the context relationship in the behavior chain. Classification only based on static labels is also difficult to reflect the change of student status in the timeline. Therefore, for the intelligent development of college students 'behavior management, it is necessary to organize data access, feature modeling, behavior recognition, status discrimination and early warning feedback in the same computing link, so that the management system has the ability of continuous perception, dynamic update and classification response.

Based on this idea, this paper focuses on the scenario of university student behavior management under the background of information technology, and constructs a computing framework that integrates multi-source data modeling, intelligent recognition algorithm and early warning decision mechanism. In the data layer, learning platform logs, access control card records, class check-in sequences, dormitory return information and campus network access fragments are unified and integrated to form a heterogeneous sample representation with time, location, event type and behavior intensity. At the method level, an intelligent algorithm oriented to the joint expression of temporal association and structural relationship is introduced to identify, cluster and discriminate student behaviors, and on this basis, the risk stratification results are generated. In the application layer, the recognition results were written back to the management end, which supported the counselors, teaching management departments and platform service modules to carry out hierarchical intervention, resource push and trajectory verification, and improved the real-time performance, consistency and traceability of behavior management.

The research content of this paper consists of four parts. The introduction part explains the computational requirements of student behavior management and related research progress. The research background section explains the source of behavior data and management scenarios. The third section expands the method design from multi-source data modeling, behavior recognition, state discrimination and early warning decision. Section IV analyzes the identification effect, management result and system performance combined with the experimental results. Finally, the discussion, conclusion and application value are given.

2 Research Background

College student behavior management is shifting from experience records to data-driven computing. Campus platform, learning management system, access control equipment, dormitory check-in terminal and network authentication system continuously generate structured and semi-structured logs, so that students 'behavior trajectories in learning, life and transaction processes can be uniformly collected, associated and modeled. Facing this change, the research focus has been extended from single score statistics to behavior recognition, state characterization, risk stratification and collaborative calculation of management feedback. Around this direction, the application of machine learning, learning analysis and deep representation methods in university scenarios has gradually deepened in recent years, and the core content of related research is shown in Table 1. From the perspective of computational methods, traditional manual verification has been gradually replaced by feature engineering, ensemble learning, temporal networks, graph structure modeling, and interpretable prediction. The data in the behavior management scenario is not a pure classification sample, but a composite event sequence with time order, spatial location, relational connection and semantic context. Therefore, it is necessary to take into account the representation ability, response speed and deployment stability. In this context, the value of computer technology is not only reflected in recognition accuracy, but also reflected in cross-system data alignment, heterogeneous feature compression, anomaly pattern retrieval and management interface linkage. The change of research background corresponds to the change of university student behavior management from record management to model driven management.

Table 1: Representative contents of intelligent research on student behavior management in colleges and universities

Reference	Research Direction	Main Content	Technical Insight
[11]	Early dropout identification	Uses machine learning to predict student performance and dropout risk	Early warning models can support hierarchical behavior management
[13]	LMS log prediction	Builds a course-independent log prediction framework	Platform logs have transferable modeling value
[14]	Learning analytics dashboard	Examines the impact of visual feedback on engagement	The management interface should support real-time feedback
[18]	Dropout prediction	Applies pretrained language models to risk identification	Text information can extend the boundary of behavior modeling
[21]	Deep learning review	Summarizes prediction methods in virtual learning environments	Temporal learning and complex feature modeling have become mainstream
[22]	Dashboard design evaluation	Studies interface design that supports learning regulation	The system side should balance display and guidance

Christou et al. conducted research on the performance and early churn identification of higher education students, and used machine learning to complete multi-index prediction, indicating that behavioral data had stable early warning value [11]. Lopez-Garcia et al. proposed an early detection method for student failure, which inputted multi-class learning features into the classification model to realize rapid recognition at the course level [12]. Santos and Henriques proposed a class-independent LMS log prediction framework, emphasizing the timeliness and transferability of the model [13]. Ramaswami et al. studied the influence of learning analytics dashboard on the growth of engagement and proved that visual feedback can improve the level of student interaction [14]. Chen et al. analyzed the behavior of students in using learning analytics dashboards in higher education and revealed the association between operational paths and learning performance [15]. Ifenthaler et al. investigated students' use of self-assessment based on learning analysis, and proposed that behavior records could support more fine-grained learning state judgment [16].

Xing et al. used learning analysis to explore the multi-dimensional participation structure in collaborative learning, and incorporated communication frequency, collaboration depth and task contribution into a unified analysis framework [17]. Won et al. proposed a college dropout prediction method based on pre-trained language model, which introduced text features into the risk identification process and expanded the input boundary of student state modeling [18]. Nayak et al. constructed a classification model of students' academic performance through educational data mining, and verified the enhancement effect of multi-source feature fusion on prediction performance [19]. Tzimas and Demetriadis studied the influence of learning analysis guidance on self-regulation, performance and satisfaction, indicating that a more complete behavioral intervention chain can be formed after the analysis results enter the feedback link [20]. Alnasyan et al. systematically reviewed the research progress of deep learning to predict student performance in virtual learning environment, and pointed out that time series modeling and complex feature learning have become important directions [21]. De Vreugd et al. further studied the analysis dashboard supporting learning regulation from the perspective of design and evaluation, indicating that the management system is no longer just a data display terminal, but a behavior guidance interface [22].

The above studies have promoted the transformation of university student data analysis from result judgment to process calculation, and also promoted the management objects from static labels to dynamic states. However, existing work mostly focuses on a single course platform, specific learning tasks or local early warning scenarios, and the expression of cross-source correlation between classroom behaviors, access trajectories, dormitory work and rest, platform interactions and abnormal events is still insufficient. Some researches focus on the prediction results themselves, but less on the management state hierarchy, early warning rule writeback and system cascade support. For the intelligent development of college students 'behavior management under the background of information technology, it is necessary to build a computable behavior representation mechanism on a unified data base, and organize recognition, discrimination and feedback as a continuous process. Based on this, it is necessary to design the system from three levels: multi-source data modeling, intelligent algorithm identification and early warning decision collaboration.

3 The intelligent development of college students 'behavior management under the background of information technology

3.1 Multi-source data modeling and feature representation Method for college student behavior Management

College student behavior management involves multiple data sources such as learning platform access, class check-in, access control, dormitory return to bed and campus network authentication. The record granularity, sampling frequency and field semantics of different systems are not consistent, so the original log cannot be directly entered into the unified discrimination process. In order to ensure the stability of subsequent behavior recognition and management state discrimination, this paper completes heterogeneous log access, time alignment, event mapping and sample organization in the data layer, and then converts discrete records into computable behavior representation through unified coding. In this process, the original records are not simply spliced, but a unified sample tensor is constructed on the basis of preserving the time order, spatial location and event semantics, so that the behavior changes in the management scene can be expressed in the same feature space.

As shown in Fig. 1, the multi-source data modeling process consists of six parts: data access, event cleaning, time alignment, cross-source fusion, feature encoding, and sample generation. The data access layer is responsible for receiving learning platform logs, access control records, dormitory return records, classroom check-in information and campus network access records. The event cleaning layer is used to eliminate outliers, unify fields and compress duplicate logs. The time alignment layer reorganizes cross-platform event sequences according to a unified time window. The cross-source fusion layer maps the records from different sources into student-level behavior fragments. The feature encoding layer is responsible for generating continuous features and discrete embeddings. The sample generation layer outputs standardized inputs required for subsequent model training and online discrimination. This process ensures that the data of different time periods, different scenarios and different systems can be uniformly organized, and provides stable input for subsequent intelligent algorithms.

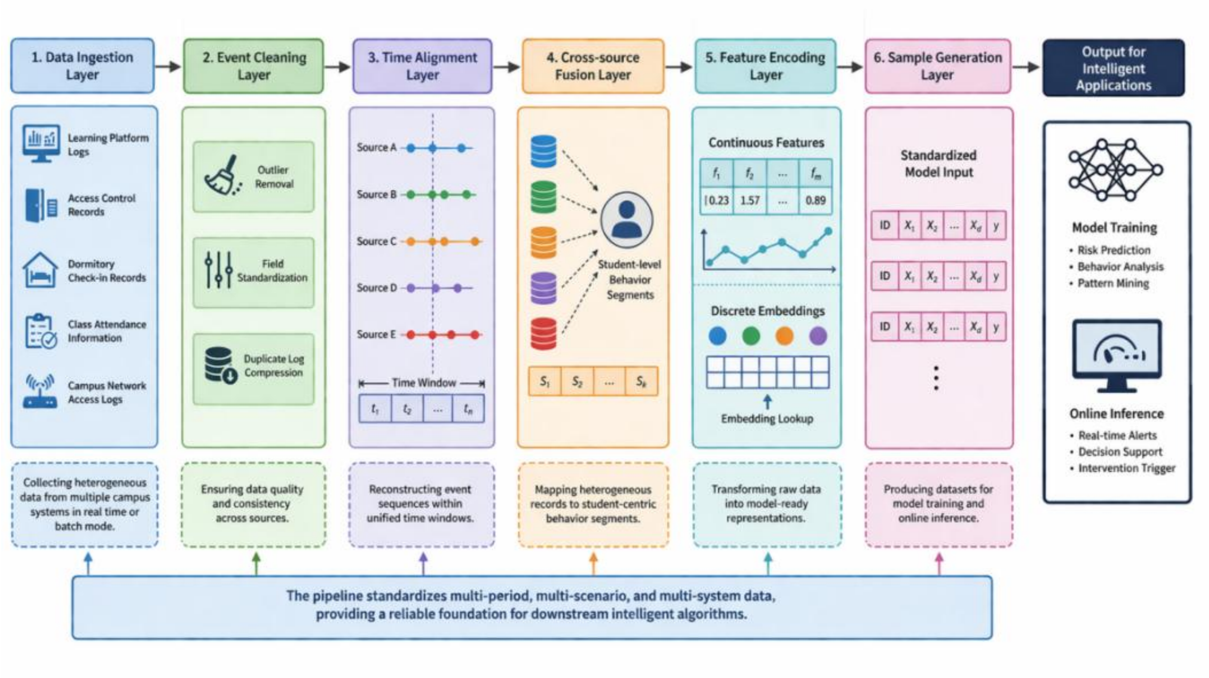

Figure 1: Modeling process of multi-source behavioral data of college students

In order to realize the unified access coding of the learning platform access control dormitory classroom and network log, this paper uses the following fusion calculation method to generate the basic input representation result item:

$$X_i^t = [x_i^{lms} \| x_i^{acc} \| x_i^{dor} \| x_i^{net} \| x_i^{cls}] \tag{1}$$

where X_i^t represents the fused input vector of student i in time window t; Behavior characteristics of x_i^{lms} representation learning platform; x_i^{acc} represents the access control traffic characteristics; x_i^{dor} represents the dormitory work and rest characteristics; x_i^{net} represents the campus network access characteristics; x_i^{cls} represents class check-in and class participation features; $\|$ denotes the vector concatenation operation. Equation (1) is used to map student behavior records scattered in different business systems into the same input space, which provides the basis for subsequent representation learning.

Only using static stitching cannot reflect the time distance of behavior events. Therefore, this paper further introduces a time attenuation mechanism to assign different weights to the events in the window, so that the recent behavior maintains a higher contribution in the modeling process.

In order to highlight the actual impact of recent behavior on the dynamic change of student management status, this paper uses the following time attenuation calculation method to complete the whole process of weight allocation modeling:

$$\omega_k = \frac{\exp(-\lambda \Delta t_k)}{\sum_{r=1}^{n} \exp(-\lambda \Delta t_r)} \tag{2}$$

Here, ω_k represents the time contribution weight of the k event. Δt_k represents the time interval between the event and the current discriminative moment; Let λ denote the time decay coefficient; n denotes the number of events in the current time window. Equation (2) is used to enhance the influence of recent actions on state modeling and maintain the temporal sensitivity of student state changes.

After completing the time weighting, discrete behavior events, statistical counting features and time attributes are jointly fed into the projection layer to form a unified implicit representation. This representation not only preserves the behavior frequency information, but also retains the semantic differences of behavior types, so that data from different sources can be compressed and aligned in the same representation space.

In order to compress the continuous statistical information and the discrete event semantic information in the same space, we use the following joint projection calculation method to generate the behavior latent representation result value:

$$h_i^t = \sigma\left(W_x X_i^t + W_v \sum_{k=1}^{n} \omega_k v_k + b\right) \tag{3}$$

Here, h_i^t represents the implicit representation of student i behavior in time window t. W_x and W_v denote the feature mapping matrix; v_k represents the semantic embedding vector of the k event;b represents the bias term; Let $\sigma(\cdot)$ denote the nonlinear activation function. Formula (3) is used to compress the continuous statistics and discrete semantic information into a unified latent space, so as to provide a compact and stable feature basis for subsequent state discrimination.

As shown in Fig. 2, the feature representation module is organized in a dual-branch way. The left branch is responsible for processing continuous statistics such as access times, online duration, access frequency, check-in interval and return to bed offset, and the right branch is responsible for processing discrete event embedding such as lateness, absence, abnormal access at night, low activity access and sudden centralized login. The two branches complete the fusion at the joint projection layer and subsequently enter the context enhancement unit to form the final representation with group association information. This structure avoids information dilution caused by simple concatenation, and also enhances the adaptability of behavior representation to complex management scenarios.

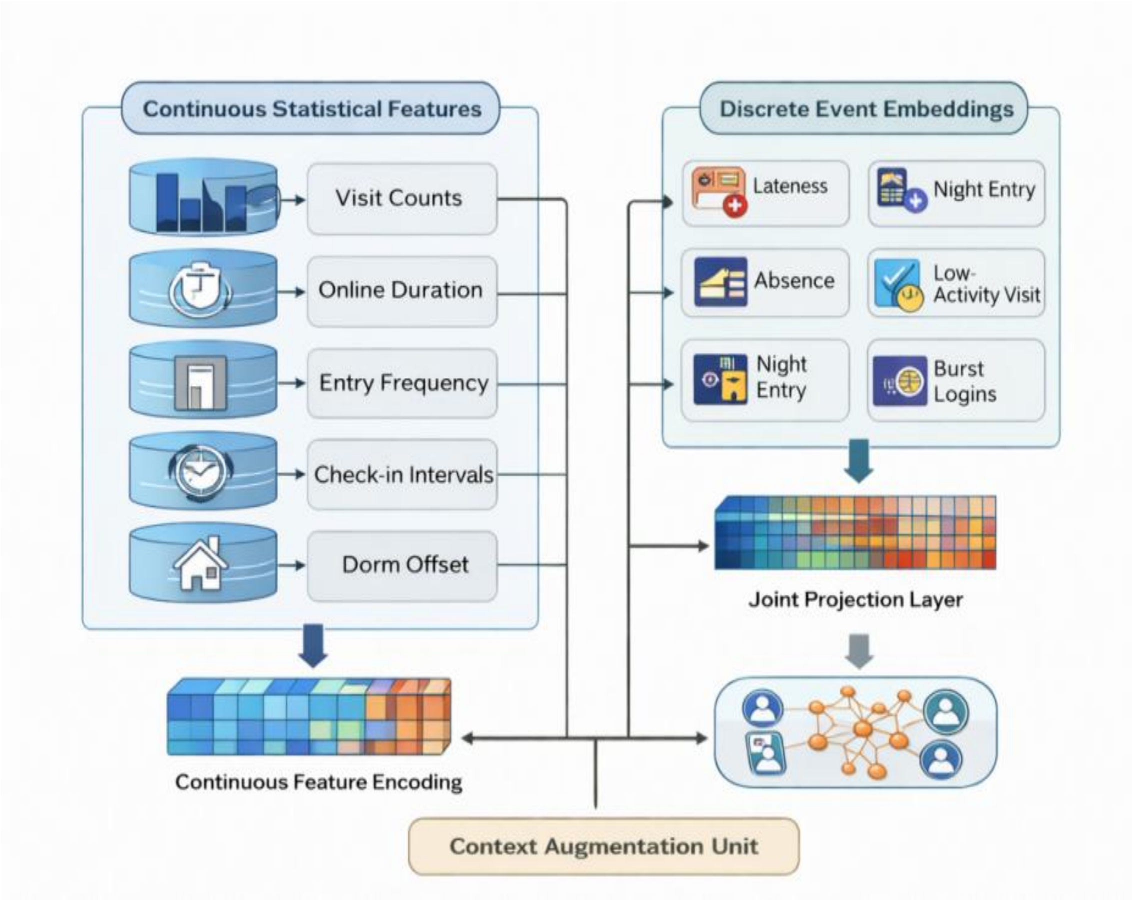

Figure 2: Multi-source behavioral feature representation module structure

Considering that there are also relationships among students in class, course, dormitory and activity space, this paper further constructs the student behavior relationship graph based on implicit representation, and uses the attention propagation method to extract local context information. In this way, the isolated samples can be put into the group environment for joint modeling, and the interference of single point fluctuations on the state description can be reduced.

In order to depict the association characteristics between students in the course, class, dormitory and spatial activities, this paper uses the following relationship enhancement calculation method to complete the context modeling processing:

$$z_i^t = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} h_j^t, \quad \alpha_{ij} = \frac{\exp(\phi(h_i^t, h_j^t))}{\sum_{m \in \mathcal{N}(i)} \exp(\phi(h_i^t, h_m^t))} \tag{4}$$

Here, z_i^t represents the enhanced representation after relation propagation; $\mathcal{N}(i)$ represents the set of neighborhood nodes of student i; Let α_{ij} denote the influence weight of neighbor node j on student i; Let $\phi(\cdot)$ denote the similarity function; h_j^t represents the behavior implicit representation of the neighborhood node in the current time window. Equation (4) is used to characterize the local association structure among students, so that the behavior representation absorbs group context information while preserving individual differences.

In the sample generation stage, the fixed-length sliding time window is used to construct the training instance, and the mask vector is set for the missing field to retain the original missing information. Repeated events are compressed and merged according to source confidence and temporal proximity, and abnormal events are kept their frequency and burst strength separately to avoid rare patterns being weakened in the fusion process. After the above processing, the multi-source behavior data is organized into a unified input form with temporal order, semantic category and relational structure.

3.2 College students 'behavior recognition and management status discrimination based on intelligent algorithms

After the completion of multi-source data modeling and unified feature representation, student behavior recognition needs to further deal with the time dependence, spatial correlation and category boundary information in the event sequence. Different from static rule matching, the intelligent algorithm can extract behavior evolution trajectories from continuous logs, and map patterns such as class-to-class anomalies, nighttime abnormal access, low activity of the platform, continuous missing intersections, and sudden centralized access into discriminative state labels. In this paper, temporal coding, attention aggregation and two-branch discriminative structures are introduced in the recognition layer, so that the individual behavior segments and the group context work synergistically in the same computing framework, so as to improve the consistency of recognition results and the stability of management state discrimination.

As shown in Fig. 3, the action recognition module consists of sequence encoding unit, relation enhancement unit, category discrimination unit and state mapping unit. The sequence encoding unit is responsible for the position encoding and time convolution of continuous events in the sliding time window. The relationship enhancement unit receives the course, class and dormitory adjacency relations between students to supplement the local context. The category discrimination unit output behavior categories such as abnormal classroom attendance, abnormal work and rest, abnormal interaction and abnormal access. According to the recognition results, the state mapping unit generates three management states: normal, concern and warning. This structure avoids the excessive traction of a single event on the final result, and also enables the management side to obtain more continuous discriminant output.

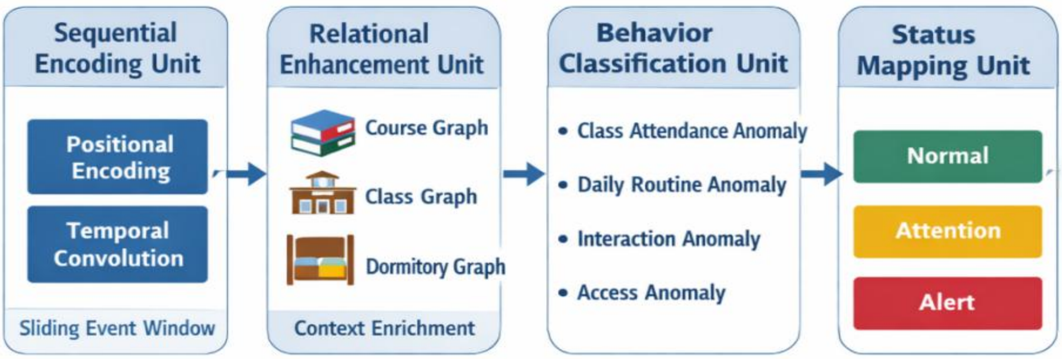

Figure 3: Overall structure diagram of student behavior recognition and state discrimination

In order to extract the local change rules of continuous behavior events in a unified time window, this paper uses the following time series encoding calculation method to complete the sequence representation learning process:

$$u_i^t = \mathrm{TCN}(H_i^t) + P_i^t \tag{5}$$

where H_i^t represents the input sequence matrix of student i in time window t; $\mathrm{TCN}(\cdot)$

denotes the temporal convolutional encoding operation; P_i^t represents the joint encoding term of position and time. u_i^t represents the behavior representation after temporal modeling. Formula (5) is used to describe the local evolution relationship of the same student in the continuous event chain, so that the behavior recognition not only depends on frequency statistics, but also can perceive the sequence and change rhythm.

It is still difficult to distinguish behavior samples with similar frequency but different evolution rhythms by only using sequential stacking. Therefore, we first use temporal convolutional network to extract local patterns, and then use position encoding to preserve the order of event occurrence. The timing coding results are further entered into the attention aggregation module, which is used to strengthen the contribution of key segments such as late concentration segments, abnormal login segments, and sleep-rest offset segments. This can reduce the dilution of high-frequency common behaviors to a small number of key abnormal behaviors, and make the recognition results closer to the real state changes in students 'daily management scenarios.

In order to highlight the dominant role of key behavior segments in the formation of recognition results, this paper uses the following attention aggregation calculation method to complete feature compression mapping processing:

$$\beta_k = \frac{\exp(q^\top \tanh(W_u u_{i,k}^t + b_u))}{\sum_{r=1}^{m} \exp(q^\top \tanh(W_u u_{i,r}^t + b_u))}, \quad g_i^t = \sum_{k=1}^{m} \beta_k u_{i,k}^t \tag{6}$$

Here, β_k represents the attention weight of the k behavior segment. $u_{i,k}^t$ denote the local fragment representation after temporal encoding; W_u and b_u denote mapping parameters; q denotes the attention query vector; g_i^t represents the aggregated individual behavior characteristics. Formula (6) is used to enhance the contribution of key behavior segments in the overall representation, so that the abnormal patterns can maintain sufficient identification in long sequences.

Relying on individual sequences alone is still not enough to distinguish similar samples in different group environments, so this paper continues to write the connections in class, dormitory, course and activity Spaces into the graph propagation process. The relationship enhancement layer absorbs neighborhood information while preserving individual differences, so that patterns such as night return in the same dormitory, low activity in the same course and abnormal absence in the same class can be identified more stably. Instead of replacing individual features with group averages, the proposed method modifies the explanatory strength of isolated events in a contextual framework, thereby reducing the state drift caused by accidental perturbations.

In order to incorporate the neighborhood influence in the classroom dormitory courses and activity space into the overall discrimination, this paper uses the following graph propagation calculation method to complete the context enhancement modeling processing:

$$r_i^t = \sigma\left(\sum_{j\in\mathcal{N}(i)} \frac{A_{ij}}{\sqrt{d_i d_j}} W_r g_j^t + b_r\right) \tag{7}$$

Here, A_{ij} represents the neighboring weights between student nodes. d_i and d_j denote the degree value of the corresponding node; W_r denotes relation propagation matrix; b_r denotes the bias term; r_i^t represents the context feature after relationship enhancement. Let $\sigma(\cdot)$ denote the nonlinear activation function. Equation (7) is used to absorb the common activity characteristics of students in the same group and reduce the fluctuation of isolated samples in state discrimination.

Furthermore, administrative states are not directly equivalent to behavioral categories. Class absence may only be an ordinary fluctuation in a short window. If it occurs at the same time with late return of dormitory, platform stagnation and abnormal access control, the state risk will increase significantly. Based on this feature, we introduce the idea of multi-label collaborative discrimination in the state mapping stage, and input the identification label, neighborhood context and time continuity into the state hierarchical module together, so that the management label can be dynamically updated with the change of the chain. The design enhances the business interpretation of the results, and facilitates the subsequent system to trigger differentiated reminder, verification and intervention processes according to different status levels.

As shown in Fig. 4, the output is designed with two branches. The classification branch is responsible for giving fine-grained behavior labels, and the status branch is directly oriented to the management end to output three-level results: normal, concern and warning. The two branches share the front-end timing and relational encoding results, but constrain the recognition accuracy and state stability respectively on the objective function. The shared structure ensures that the two types of outputs have the same data source, and the branch structure ensures that the behavior category and the management state can maintain their own clear discrimination boundary.

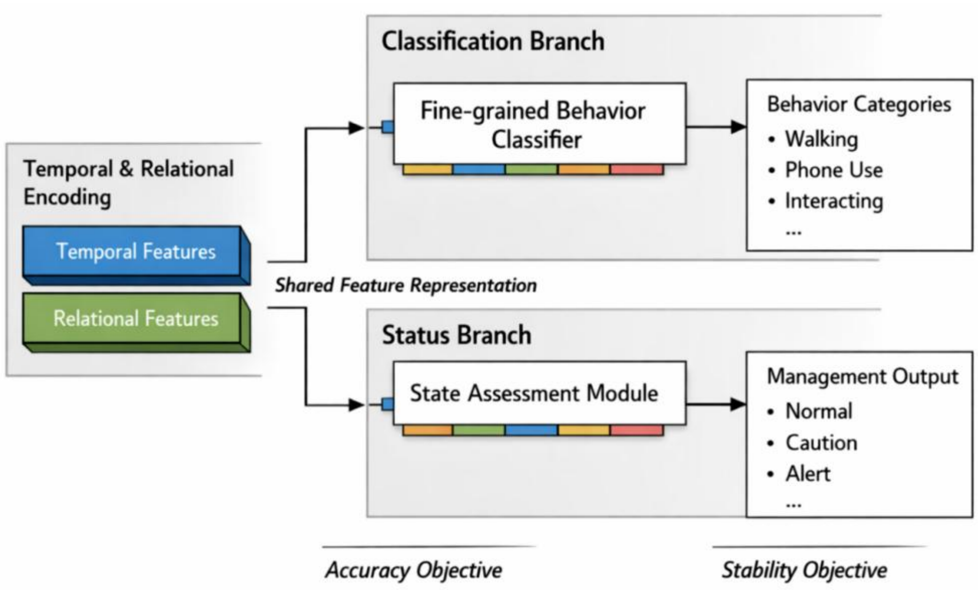

Figure 4: Dual-branch behavior recognition and management state mapping structure diagram

In order to accomplish the two task objectives of behavior category recognition and management status stratification synchronously, this paper uses the following joint output calculation method to construct the dual-branch prediction result value:

$$\hat{y}_i^t = \mathrm{softmax}(W_c[g_i^t \| r_i^t] + b_c), \quad \hat{s}_i^t = \mathrm{softmax}(W_s[g_i^t \| r_i^t] + b_s) \tag{8}$$

where $\hat{y}_i^t$ represents the behavior category prediction result; $\hat{s}_i^t$ represents the management state prediction results. W_c and W_s represent the output matrices of the two branches; b_c and b_s denote the bias terms; $\|$ denotes the feature concatenation operation. Formula (8) is used to complete fine-grained behavior recognition and management state discrimination on the same feature base, so as to ensure that the results have a consistent semantic source.

At the same time, the model output is also subjected to temperature calibration and threshold smoothing before entering the management end, in order to weaken the perturbation of instantaneous spikes on the results. In this way, it can not only retain the sensitive response of abnormal behavior, but also avoid the frequent jump of the state label between adjacent time Windows, and ensure that the system output is more stable. This processing method is more suitable for the continuous operation requirements of the daily management platform in colleges and universities, and also improves the availability of result writeback and early warning linkage.

In order to take into account the comprehensive influence of classification accuracy state stability and class distribution difference, this paper uses the following joint loss calculation method to complete the whole process of model training and optimization:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\mathrm{cls}} + \lambda_2 \mathcal{L}_{\mathrm{state}} + \lambda_3 \sum_{c=1}^{C} (1 - p_c)^{\gamma} y_c \log p_c + \lambda_4 \|W\|_2^2 \tag{9}$$

Here $\mathcal{L}_{\mathrm{cls}}$ represents the action category cross-entropy loss; $\mathcal{L}_{\mathrm{state}}$ represents the management state discrimination loss; p_c is the class c prediction probability. y_c corresponds to the true label; Let γ denote the adjustment coefficient for difficult samples. $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the loss weights; $\|W\|_2^2$ denotes the parametric regularization term. Equation (9) is used to simultaneously constrain the recognition accuracy, the state boundary, and the class balance, so that the model can maintain a more robust discriminative ability in complex campus behavior scenarios.

After the above design, the student behavior recognition no longer stays at the single-point log classification level, but forms a continuous calculation process composed of timing coding, attention aggregation, relationship propagation and double-branch output, which provides reliable input for the subsequent early warning decision mechanism.

3.3 Intelligent management framework of college student behavior integrated with early warning decision mechanism

After the completion of behavior recognition and state discrimination, student behavior management also needs to convert the classification results into executable early warning instructions. Pure output of abnormal labels can only reflect local fluctuations, which is difficult to directly support counselor verification. This paper constructs an intelligent management framework that integrates the early warning decision mechanism, which integrates the behavior label, state level, time continuity and group deviation information into the risk decision-making process. The framework formed a closed-loop computing link through five steps: risk pooling, state transition, threshold adaptation, priority sorting and feedback update.

As shown in Fig. 5, the intelligent management framework consists of a risk convergence layer, a state transition layer, a threshold adjustment layer, an early warning ranking layer, and a feedback update layer. The risk aggregation layer receives the probability results output by the behavior recognition branch and the management state branch, and combines the cumulative offset in the time window to form a continuous risk score. The state transition layer judged the transition between normal, concern and warning according to the change of adjacent time Windows. The threshold adjustment layer combined with class density, dormitory activity and course weekly to correct the trigger boundary. The early warning sorting layer generates the disposal priority based on the risk intensity, impact range and duration. The feedback update layer writes the verification results back to the cache, which is used to modify the subsequent warning strategy. The framework makes student behavior management change from static recognition to continuous decision-making.

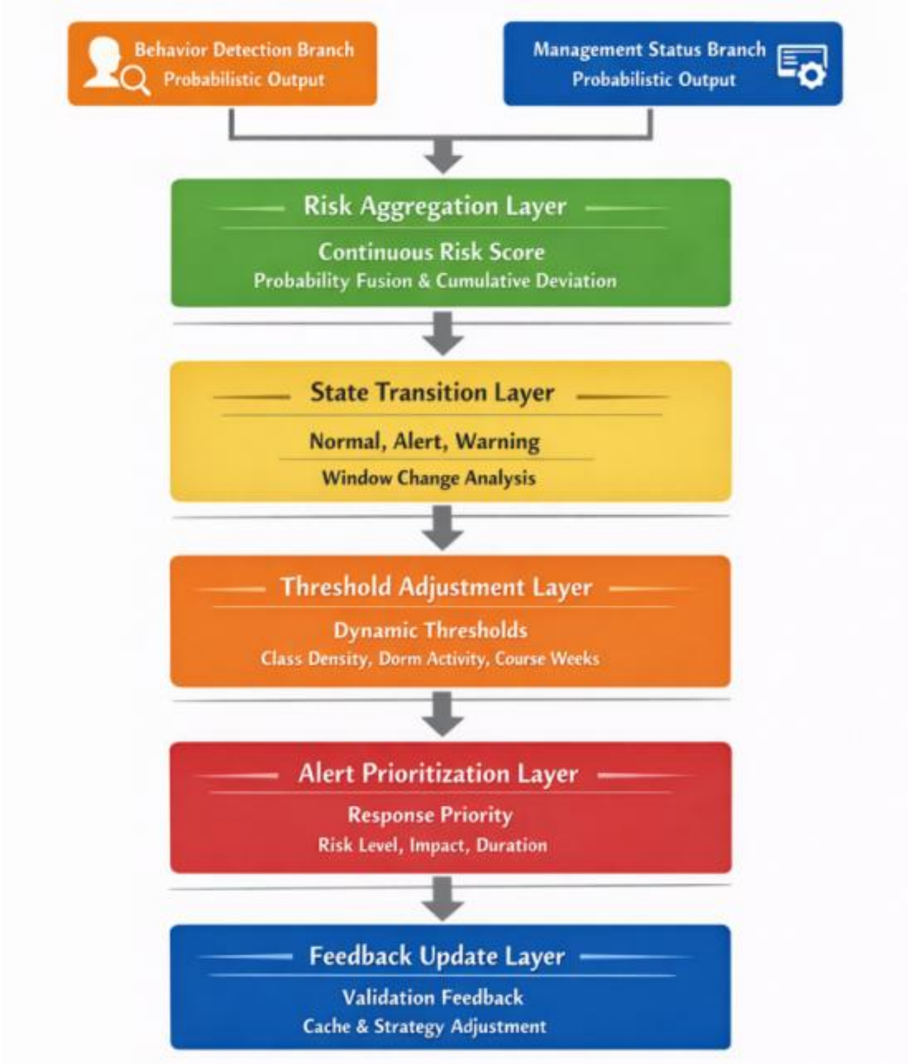

Figure 5: Intelligent management framework of college student behavior with early warning decision mechanism

In order to map multiple types of abnormal behavior and state discrimination results into risk scores, this paper uses the following weighted aggregation method to generate comprehensive early warning score results:

$$R_i^t = \sum_{c=1}^{C} \alpha_c p_{i,c}^t + \beta_1 q_{i,2}^t + \beta_2 q_{i,3}^t + \beta_3 \eta_i^t \tag{10}$$

Here, R_i^t represents the comprehensive risk score of student i in time window t. $p_{i,c}^t$ denote the predicted probability of class c anomaly; $q_{i,2}^t$ and $q_{i,3}^t$ denote the probability of attention and warning states, respectively. Let η_i^t denote the cumulative offset strength; α_c, β_1, β_2,β_3 denote the weight coefficients. Equation (10) is used to compress the recognition results into a uniform score.

In order to describe the continuous change process of student management status in adjacent time Windows, this paper uses the following state transition calculation method to complete the dynamic discriminant modeling process:

$$\Pi_i^t = \mathrm{softmax}(W_\pi[R_i^t, \Delta R_i^t, \ell_i^t]^\top + b_\pi) \tag{11}$$

Here, Π_i^t represents the state transition probability vector corresponding to student i at time window t. ΔR_i^t represents the difference between the current risk score and the risk score of the previous time window. ℓ_i^t denotes the anomaly persistence length; W_π and b_π denote the mapping parameters. Formula (11) is used to describe the dynamic evolution relationship among the three types of management states.

In order to automatically adjust the range of warning trigger boundary according to the difference of group activity, this paper uses the following threshold adaptive calculation method to complete the whole process of strategy modification modeling:

$$\tau_g^t = \mu_g^t + \kappa\sigma_g^t + \rho\frac{n_g^{abn}}{n_g} \tag{12}$$

Here, τ_g^t represents the dynamic threshold of population g under time window t. μ_g^t and σ_g^t denote the mean and standard deviation of the risk distribution of the population, respectively. n_g^{abn} is the number of abnormal samples in the population; n_g represents the total number of samples in the population; Let κ and ρ denote the regulation coefficients. Equation (12) is used to improve the adaptivity of early warning triggering.

In order to serially and quantitatively sort the disposal order of different student objects, this paper uses the following priority score calculation method to complete the whole process of linkage scheduling modeling:

$$P_i^t = \xi_1 R_i^t + \xi_2 \log(1 + \ell_i^t) + \xi_3\chi_i^t + \xi_4\upsilon_i^t \tag{13}$$

where P_i^t represents the disposal priority score of student i; ℓ_i^t denotes the anomaly persistence length; χ_i^t denotes the correlation range coefficient; υ_i^t represents the historical sensitivity coefficient; Let ξ_1 to ξ_4 denote the ranking weights. Equation (13) is used to unify the risk intensity, duration and impact scope into the same scheduling scale.

Only getting priority results is not enough to form a closed-loop management. The system also needs to continuously revise policy parameters according to the verification feedback. When the manual verification results deviate from the system warning, the feedback update layer will write the verification label back to the cache, and modify the risk threshold and priority weight synchronously. This can reduce local false positives and enhance scene adaptation.

In order to continuously revise the model cache and early warning policy parameters according to the verification results, this paper uses the following feedback update calculation method to complete the whole process of closed-loop adjustment modeling:

$$\theta^{t+1} = (1-\nu)\theta^t + \nu\left[\theta^t - \gamma\nabla_\theta\left(\frac{1}{M}\sum_{i=1}^{M}(y_i^{ver} - \hat{s}_i^t)^2 + \omega\left|\tau_g^{t+1} - \tau_g^t\right|\right)\right] \tag{14}$$

Here, θ^t denotes the set of policy parameters at time t; Let ν denote the feedback fusion coefficient; Let γ denote the update step; M represents the current number of verification samples; y_i^{ver} indicates the manual verification label; $\hat{s}_i^t$ represents the output state value of the system. Let ω denote the threshold smoothing coefficient. Equation (14) is used to progressively update the policy parameters using the verification results.

Under the above mechanism, the recognition result, status score and verification feedback are organized as a continuous closed loop. Risk aggregation ensures that anomalies from different sources enter the same scoring space, state transition ensures that short-term fluctuations and persistent anomalies are distinguished, threshold adaptation ensures that group differences are included in the decision boundary, priority sorting ensures that limited management resources are reasonably allocated, and feedback update ensures that the system continues to correct during operation.

4 Analysis of intelligent development results of college students 'behavior management under the background of information technology

4.1 Analysis of student behavior recognition results based on multi- source behavior data modeling

Three datasets were used in this research experiment, namely CamPS-Trace, LMS-Flow and a self-built comprehensive dataset. Cample-trace is used to describe the continuous behavior records of access control, dormitory and class check-in, LMS-Flow is used to describe the course platform access, assignment submission and resource browsing trajectories, and a self-built comprehensive dataset is used to uniformly sample and time align the learning, living and spatial activity logs. The three sets of data cover five kinds of typical behaviors, such as abnormal attendance, shift of work and sleep, low active access, abnormal login and continuous missing attendance, which are used to verify the applicability of the multi-source modeling method in college student behavior recognition.

As shown in Fig. 6, the proposed model is compared with the Temporal-MLP and BiGRU baseline methods on two datasets Camfield-trace and LMS-Flow. The recognition accuracy of the proposed model in the Campus Trace dataset reaches 0.931, which is significantly higher than 0.884 of Temporal-MLP and 0.907 of BiGRU. On the LMS-Flow dataset, the recognition accuracy of the proposed model reaches 0.918, which is 0.041 and 0.026 higher than the two baselines, respectively. This result shows that the unified behavior representation formed after multi-source data modeling can more stably preserve the time order and event semantics, and also shows that the constructed feature space is more suitable for handling category boundaries in cross-system logs.

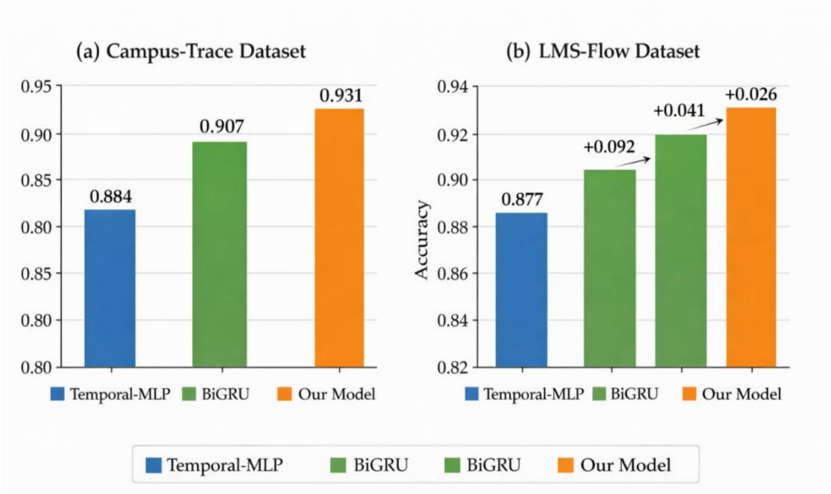

Figure 6: Comparison of student behavior recognition results under different datasets

On the self-built synthetic data set, the model further shows stronger stability. Since this dataset contains four kinds of source records at the same time: classroom, dormitory, access control and platform, there is more obvious heterogeneity within the sample. If we only rely on a single source, the model is vulnerable to local missing and abnormal fluctuations. Through unified time window reconstruction and semantic embedding mapping, the interference caused by inconsistent field distribution is weakened, so that the abnormal behavior can maintain a high resolution in the same discrimination space. From the experimental process, the convergence curve of the model in the later stage of training is more stable, indicating that the multi-source behavior representation has better robustness in complex campus scenes.

Based on the recognition accuracy results given in Fig. 6, this paper continues to perform dimensionality reduction visual analysis of the behavior representation of the last layer of the model to further test the feature discrimination ability after multi-source data modeling. In order to ensure the consistency of comparison, Fig. 7 selects five types of behavior samples from the self-built comprehensive data set, including abnormal attendance, delayed return to bed, low active access, abnormal login and continuous missing interaction, and randomly selects 240 records from each type, totaling 1200 records, and uniformly maps them into the two-dimensional feature space for display.

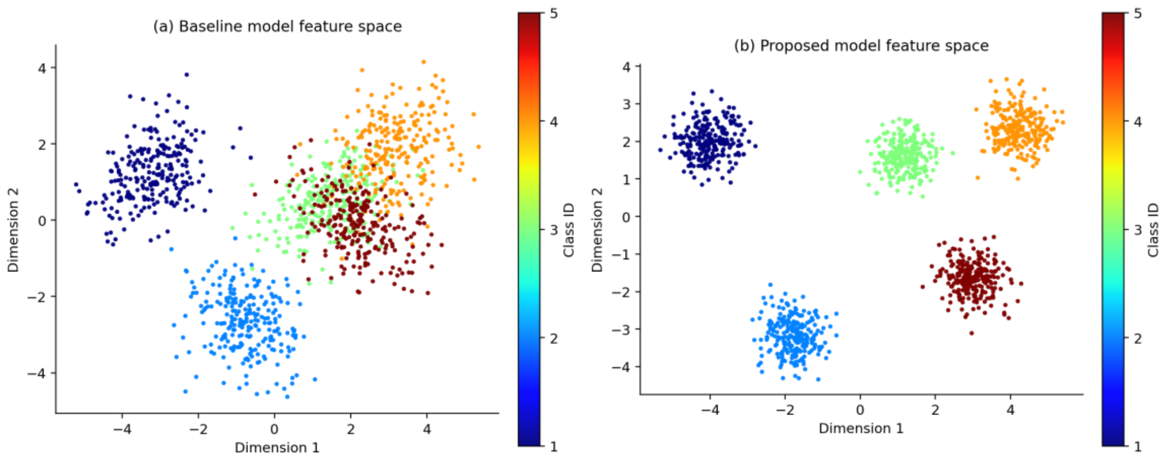

Figure 7: Distribution results of different models in the behavioral feature space

As shown in Fig. 7, the baseline model still has obvious overlapping areas between the samples of low active access and continuous missing intersection, and the boundaries of abnormal login and attendance are also scattered, indicating that the single time series modeling is still not sufficient to express the cross-source behavior differences. In contrast, the clustering centers of the proposed model on the five types of behaviors are more concentrated, and the inter-class intervals are clearer. After dimension reduction, the silhouette coefficient increases from 0.41 of the baseline model to 0.58, and the Davies-Bouldin index decreases from 1.37 to 0.86, indicating that the intra-class compactness and inter-class separation are significantly improved after multi-source feature joint modeling. In particular, the center distance of the proposed model is expanded from 1.84 to 2.67 for the two confusing behaviors of bedtime delay and low active access, indicating that temporal alignment, semantic embedding, and relationship enhancement together strengthen the ability of the model to recognize fine-grained differences.

Combining the two sets of experimental results, it can be seen that the student behavior recognition method based on multi-source behavior data modeling maintains high accuracy and stable feature discrimination ability under different data conditions, which provides reliable input for the subsequent early warning decision mechanism. From the category level, the identification boundary between abnormal attendance and abnormal login is the most clear. There is a local intersection between bedtime delay and low active access in the initial stage, but they gradually separate after the joint constraint of multi-source features, indicating that temporal alignment and semantic embedding jointly enhance the ability of the model to distinguish similar behaviors, and make the sample distribution in the comprehensive data more stable. This result is consistent with the change trend of recognition accuracy mentioned above, and also verifies the effectiveness of the modeling.

4.2 Analysis of intelligent management results of student behavior with early warning decision mechanism

This study further analyzes the effect of intelligent management of student behavior after the integration of early warning decision mechanism. The experiment still uses Camps-Trace, LMS-Flow and self-built comprehensive data sets, and the above behavior recognition results are connected to the risk aggregation, state transition and threshold adaptation modules to test the continuous response ability of the system in real management scenarios. In order to facilitate comparison, this paper selects Cample-Trace and self-built comprehensive data sets as the main display objects. The former is used to test the state stratification effect in scenarios with clear rules, and the latter is used to test the stability of early warning decision under multi-source heterogeneous conditions.

As shown in Fig. 8, this paper presents the confusion matrix results of the two datasets on the three management states of normal, concern and warning. Fig. 8 (a) reflects the state discrimination effect on Camfield-Trace, and Fig. 8 (b) reflects the state discrimination effect on the synthetic dataset. The two groups of results show that the response of the diagonal region is the most concentrated, which indicates that the system can stably map the action recognition results into management states after the integration of the early warning decision mechanism. In the Cample-Trace dataset, the accuracy of normal state discrimination reaches 94.2%, concerned state reaches 90.8%, and early warning state reaches 92.6%. In the comprehensive data set, the discrimination accuracy of the above three types of states is 92.9%, 89.7% and 91.4%, respectively. Compared with the baseline system that only uses the identification branch to directly output the status label, the macro-average F1 value of the proposed method on the comprehensive data set is improved from 0.861 to 0.907, indicating that risk pooling and threshold adjustment jointly enhance the consistency of management results.

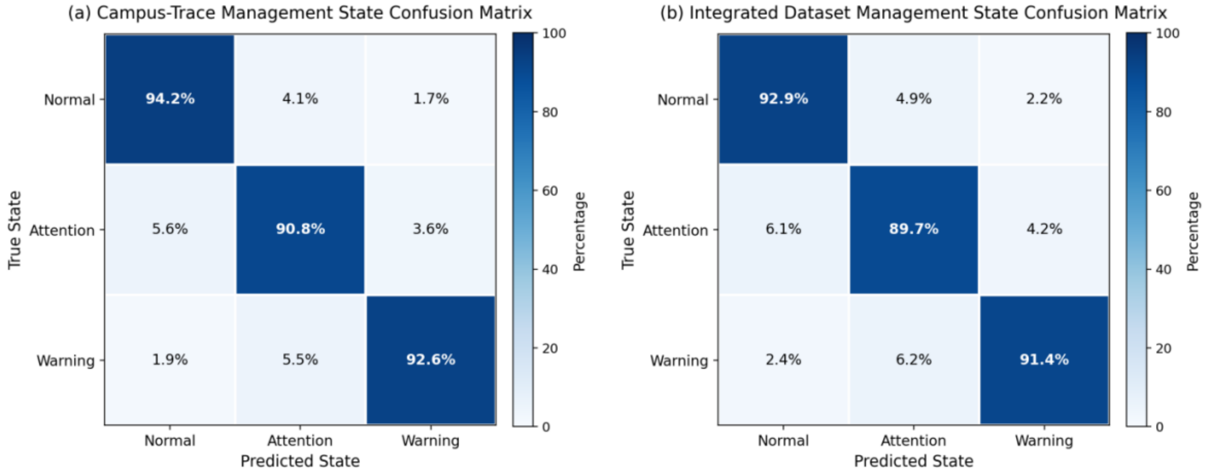

Figure 8: Discrimination results of student behavior management status under different data conditions

The results reflected in Fig. 8 show that the early warning decision mechanism is not simply superimposed after the identification module, but completes the state correction under the joint action of time continuity, group offset degree and abnormal persistence length. For the samples with single absence but normal behaviors of dormitory and platform, the system mostly determined as the attention state. For the samples that are continuously absent from work and accompanied by abnormal access at night, low activity of the platform, and abnormal access track, the system will stably classify them into the warning state. This processing method is closer to the actual operation logic of college student behavior management, and also reduces the probability of over-warning triggered by single-source anomalies.

Based on the overall state results given in Fig. 8, this paper continues to perform visual analysis of typical disposal objects in the intelligent management process to further illustrate the impact of the early warning decision mechanism on the management effect. Fig. 9 selects five types of high-frequency management events in the comprehensive data set, including continuous absence from work, delayed return to bed, abnormal login, low active access and centralized missing interaction, and uses the grouped box diagram to show the distribution differences of different events in the three-level management status score. In the figure, the box reflects the median and the upper and lower quartile range, the whisker line reflects the non-abnormal fluctuation range, and the outliers correspond to a small number of special samples that deviate from the main distribution. Therefore, the concentration degree and discrete characteristics of various events in the discrimination of management states can be intuitively presented.

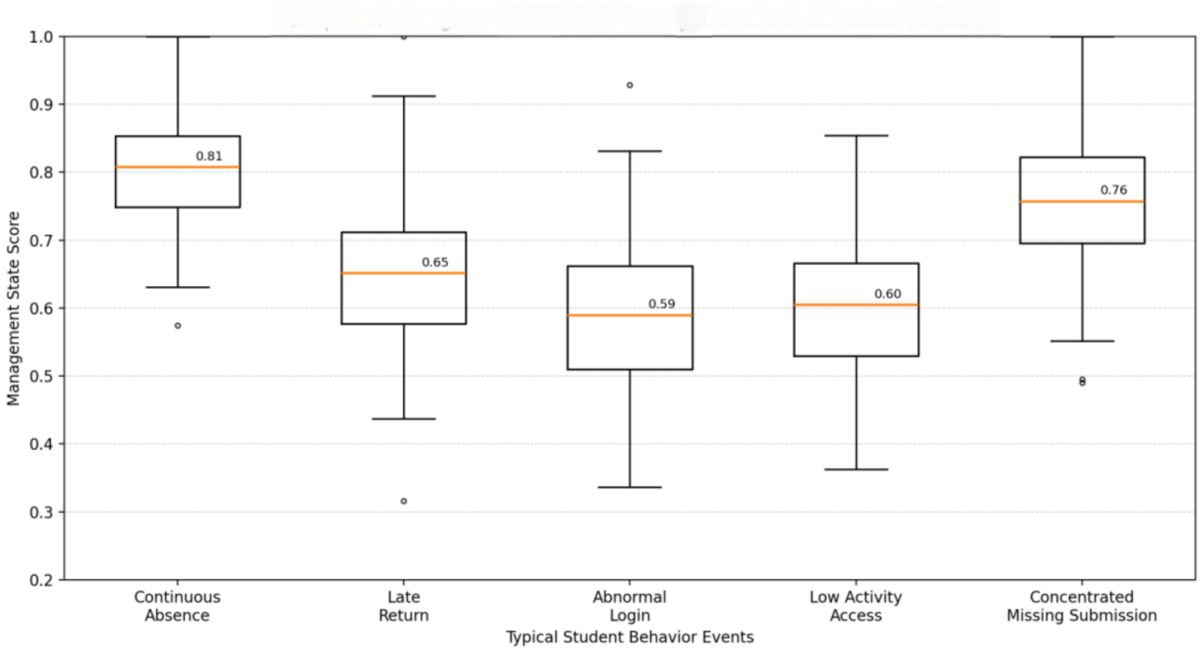

Figure 9: Results of box distribution of typical student behavior events in administrative status ratings

As shown in Fig. 9, the status score corresponding to continuous absence is the highest overall, with a median of 0.81 and an upper quartile of 0.88, indicating that such events have strong stability in early warning discrimination. The median of returning-to-sleep delay was 0.64, and the boxes were mainly distributed in the attention state interval, indicating that the system maintained a moderate intensity response to the shift of sleep and sleep. The median of abnormal login and low active access were 0.59 and 0.61, respectively, and the span of the boxes was relatively close, indicating that the two types of events had similar risk level distribution on the management side. The median of missing intersections in the cluster was 0.76, and the position of the upper whisker was higher, which reflected that this kind of behavior was easier to enter the high-risk discrimination interval. On the whole, after the integration of the early warning decision mechanism, the system no longer stays at the output of behavior categories, but can form the distribution results of state scores connected with management and disposal. At the same time, the state volatility of the system under the seven-day sliding window decreases from 0.173 of the baseline method to 0.098, and the manual verification consistency rate after early warning writeback reaches 93.5%, which further shows that the framework has good online deployment value and operation stability.

4.3 Comparative analysis of system performance of fusing early warning decision mechanism

In order to further evaluate the comprehensive performance of the system in college student behavior management scenarios, this paper compares the proposed fusion early warning decision mechanism with Rule-Score, BiGRU-Alert and Graph-Risk methods. The comparison metrics include state discrimination accuracy, macro average F1 value, early warning writeback consensus rate and average response delay. The test environment was consistent, and 20 rounds of repeated experiments were completed on the self-built comprehensive data set and Camfield-trace data set to verify the stability and transferability of the system.

As shown in Fig. 10, Fig. 10 (a) shows the state thermal profile on the Camps-Trace dataset, and Fig. 10 (b) shows the state thermal profile on the synthetic dataset. On the Camfield-trace dataset, the state discrimination accuracy of the system reaches 93.4%, and the macro-average F1 value reaches 0.914. On the synthetic dataset, the accuracy reaches 91.8%, and the macro-average F1 value is 0.903, which are 1.9 percentage points and 0.021 higher than those of the Graph-Risk method, respectively. This indicates that after the integration of risk pooling, state transition and threshold adaptation, the system has a stronger ability to interpret the behavior sequence and is more suitable for handling heterogeneous events.

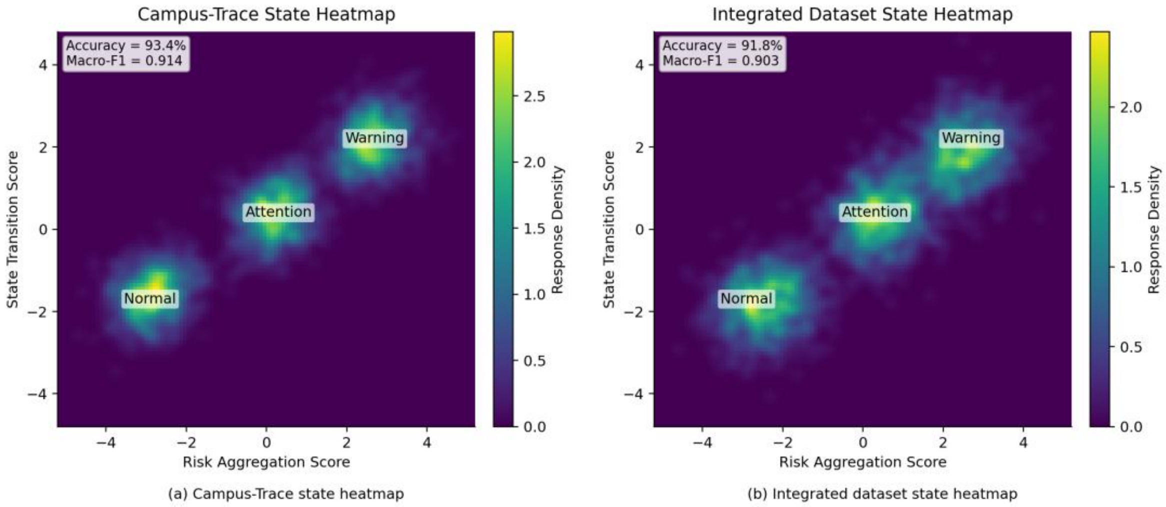

Figure 10: Comparison of system state discrimination results under different data conditions

Based on the overall comparison, this paper further conducts ablation experiments. In the experiment, the risk aggregation module, the threshold adaptive module and the feedback update module were removed respectively, and the changes of the main indicators on the comprehensive data set were recorded. The results are shown in Table 2.

Table 2: Ablation experimental results of the fused early warning decision mechanism

Model Configuration	Accuracy	Macro-F1	Write-back Consistency Rate / %	Average Latency / ms
Full System	91.8	0.903	93.5	84
Without Risk Aggregation	88.7	0.867	89.1	79
Without Adaptive Thresholding	89.3	0.874	90.4	82
Without Feedback Update	90.1	0.881	87.8	84

Table 2 shows that the risk aggregation module has the most direct effect on the unified mapping of identification results to management states. After removing this module, the macro-average F1 value decreases by 0.036, indicating that the system's processing of boundary samples will be significantly weakened if there is no unified scoring space for multi-class anomalies. The threshold adaptive module has a more obvious effect on correcting the early warning boundary between different groups, and the overall accuracy decreases by 2.5 percentage points after removal. The feedback update module has little effect on the instantaneous delay, but has the most significant effect on the manual verification consistency rate, which indicates that the closed-loop correction mechanism can improve the consistency degree between the system output and the actual management results.

As shown in Fig. 11, this paper continues to analyze the resource distribution and response density of the system in the operation phase. Fig. 11 uses the response spatio-temporal density plot to show the trigger distribution under different time periods and different management levels. The statistical results show that the normal state samples are mainly concentrated in the period from 08:00 to 18:00, accounting for 68.4%. The samples of attention status were mainly distributed in the period from 19:00 to 22:30, accounting for 57.9%. The samples of warning state were most concentrated in the period from 22:00 to 01:00 the next day, accounting for 46.7%. In terms of event sources, continuous absence, abnormal login and centralized absence accounted for 31.5%, 24.8% and 21.9% of the total warning amount, respectively. The distribution results are basically consistent with the characteristics of the campus management period, indicating that the system output has strong explanatory power at the operational level.

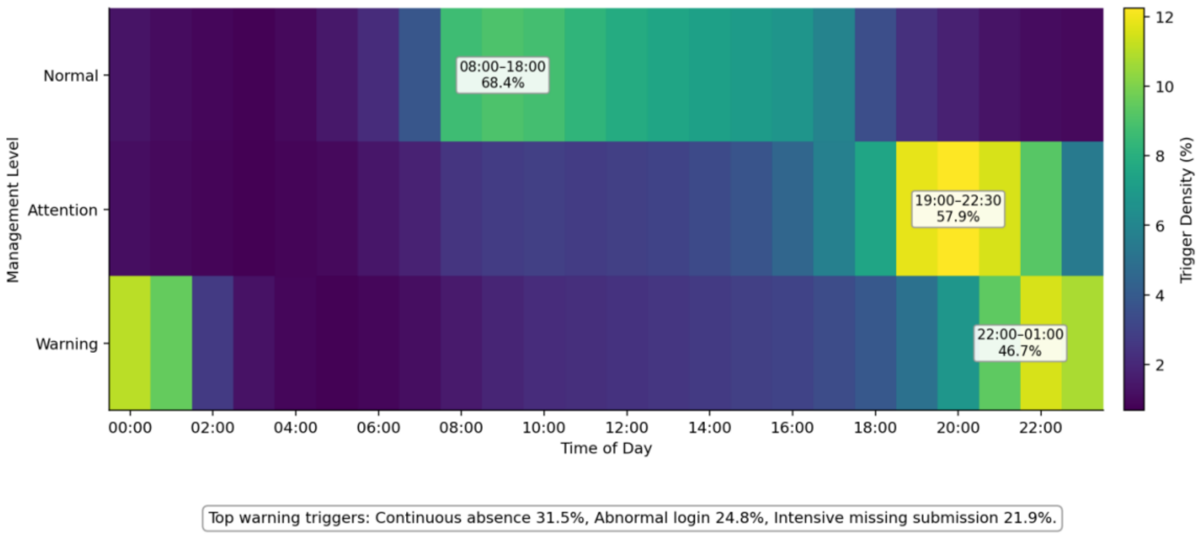

Figure 11: Response spatio-temporal density distribution of the system during the operational phase

The comprehensive comparison results, ablation experimental results and the distribution characteristics of operation stages show that the constructed system maintains good performance in three aspects: state discrimination accuracy, output stability and writeback consistency rate. The multi-source data modeling provides a unified input for cross-platform behavior information, the behavior recognition and state discrimination module ensures the mapping accuracy between abnormal categories and management levels, and the risk convergence, threshold adjustment and feedback update mechanism further strengthen the response continuity and result consistency of the system in the actual management process. The average response delay on the synthetic data set is kept within 84 ms, which indicates that the framework can meet the real-time processing requirements under online operation conditions. The above results show that the proposed method can not only complete the effective identification of student behavior, but also form a stable closed-loop support in the process of early warning generation, state stratification and result writeback.

5 Discussion

The intelligent management framework of student behavior constructed in this paper shows good technical consistency in multi-source data modeling, state discrimination and early warning decision collaboration. On the Camfield-Trace dataset, the accuracy of state discrimination reaches 93.4%, and the macro-average F1 value is 0.914. On the synthetic dataset, the accuracy and macro-average F1 value are 91.8% and 0.903, respectively, indicating that after unified time window reorganization, semantic mapping and relationship enhancement, the cross-platform behavior information can be obtained. Can form a more stable management expression. Table 2 shows that the accuracy rate drops to 88.7% and the writeback consistency rate drops to 89.1% after removing the risk aggregation module, indicating that the unified compression of recognition results to management states has a direct impact on system performance. The spatio-temporal density distribution in Fig. 11 further indicates that the system output is strongly consistent with the campus daily management rhythm, and the warning samples are mainly concentrated in the night return to bed and high-risk superposition periods. The average response delay is controlled within 84 ms, which indicates that the framework not only has good recognition ability, but also has real-time processing ability under the condition of online operation. From the perspective of calculation process, the multi-source feature representation is responsible for providing unified input, the dual-branch recognition structure is responsible for distinguishing categories and states, and the threshold adaptation and feedback update enhance the stability of the results in continuous operation. This closed-loop mechanism, which is composed of data modeling, behavior recognition, state stratification and result writeback, makes student behavior management shift from decentralized recording to continuous calculation, and provides a structural foundation for subsequent system expansion.

6 Conclusions

Focusing on the intelligent development of college students 'behavior management under the background of informatization, this paper constructs a unified computing framework composed of multi-source data modeling, behavior recognition, state discrimination and early warning decision. Experimental results show that the accuracy of the recognition method based on multi-source behavior data modeling on Camfield-trace and LMS-Flow data sets reaches 0.931 and 0.918, respectively. After integrating the early warning decision mechanism, the accuracy of state discrimination on the comprehensive data set reaches 91.8%, and the macro-average F1 value reaches 0.903. The consensus rate of manual verification reaches 93.5%, and the average response delay stays within 84 ms, which shows that the framework can support real-time recognition and hierarchical disposal in college student behavior management scenarios. The limitations of this paper are mainly reflected in two aspects. First, although the existing samples cover classroom, dormitory, access control and platform logs, the data scale across semesters, departments and campuses is still limited, and there is still room for expansion of the expression depth of complex group differences. Second, the current framework has the ability of closed-loop update, but the adaptive processing of emergencies, fluctuations in holiday behavior and long-period state drift still needs to be further enhanced. Future research will continue to expand the cross-scenario data sources, introduce more fine-grained spatio-temporal correlation features and incremental update mechanisms, and combine lightweight deployment and interpretable output design to enhance the migration ability and continuous operation ability of the system in the real campus environment. At the same time, it can also combine the federated learning strategy to improve the level of cross-departmental data collaboration and the joint modeling ability under privacy constraints, and enhance the deployment flexibility.

Funding

This work was supported by the Research Funding Project for Introduced Talents of Yichun Vocational Technical College.

References

[1] Fahd K, Venkatraman S, Miah S J, et al. Application of machine learning in higher education to assess student academic performance, at-risk, and attrition: A meta-analysis of literature[J]. Education and Information Technologies, 2022, 27(3): 3743-3775.

[2] Jang Y, Choi S, Jung H, et al. Practical early prediction of students' performance using machine learning and eXplainable AI[J]. Education and information technologies, 2022, 27(9): 12855-12889.

[3] Flanagan B, Majumdar R, Ogata H. Early-warning prediction of student performance and engagement in open book assessment by reading behavior analysis[J]. International Journal of Educational Technology in Higher Education, 2022, 19(1): 41.

[4] Susnjak T, Ramaswami G S, Mathrani A. Learning analytics dashboard: a tool for providing actionable insights to learners[J]. International Journal of Educational Technology in Higher Education, 2022, 19(1): 12.

[5] Ye D, Pennisi S. Using trace data to enhance Students' self-regulation: A learning analytics perspective[J]. The Internet and Higher Education, 2022, 54: 100855.

[6] Trakunphutthirak R, Lee V C S. Application of educational data mining approach for student academic performance prediction using progressive temporal data[J]. Journal of Educational Computing Research, 2022, 60(3): 742-776.

[7] Hellings J, Haelermans C. The effect of providing learning analytics on student behaviour and performance in programming: a randomised controlled experiment[J]. Higher Education, 2022, 83(1): 1-18.

[8] Oqaidi K, Aouhassi S, Mansouri K. Towards a students' dropout prediction model in higher education institutions using machine learning algorithms[J]. International Journal of Emerging Technologies in Learning (iJET), 2022, 17(18): 103-117.

[9] Pek R Z, Özyer S T, Elhage T, et al. The role of machine learning in identifying students at-risk and minimizing failure[J]. IEEE Access, 2022, 11: 1224-1243.

[10] Asthana P, Mishra S, Gupta N, et al. Prediction of student's performance with learning coefficients using regression based machine learning models[J]. IEEE Access, 2023, 11: 72732-72742.

[11] Christou V, Tsoulos I, Loupas V, et al. Performance and early drop prediction for higher education students using machine learning[J]. Expert Systems with Applications, 2023, 225: 120079.

[12] López-García A, Blasco-Blasco O, Liern-García M, et al. Early detection of students'

failure using Machine Learning techniques[J]. Operations Research Perspectives, 2023, 11: 100292.

[13] Santos R M, Henriques R. Accurate, timely, and portable: Course-agnostic early prediction of student performance from LMS logs[J]. Computers and Education: Artificial Intelligence, 2023, 5: 100175.

[14] Ramaswami G, Susnjak T, Mathrani A. Effectiveness of a learning analytics dashboard for increasing student engagement levels[J]. Journal of Learning Analytics, 2023, 10(3): 115-134.

[15] Chen L, Geng X, Lu M, et al. How students use learning analytics dashboards in higher education: A learning performance perspective[J]. Sage Open, 2023, 13(3): 21582440231192151.

[16] Ifenthaler D, Schumacher C, Kuzilek J. Investigating students' use of self-assessments in higher education using learning analytics[J]. Journal of Computer Assisted Learning, 2023, 39(1): 255-268.

[17] Xing W, Zhu G, Arslan O, et al. Using learning analytics to explore the multifaceted engagement in collaborative learning[J]. Journal of Computing in Higher Education, 2023, 35(3): 633-662.

[18] Won H S, Kim M J, Kim D, et al. University student dropout prediction using pretrained language models[J]. Applied Sciences, 2023, 13(12): 7073.

[19] Nayak P, Vaheed S, Gupta S, et al. Predicting students’ academic performance by mining the educational data through machine learning-based classification model[J]. Education and Information Technologies, 2023, 28(11): 14611-14637.

[20] Tzimas D E, Demetriadis S N. Impact of learning analytics guidance on student self-regulated learning skills, performance, and satisfaction: A mixed methods study[J]. Education Sciences, 2024, 14(1): 92.

[21] Alnasyan B, Basheri M, Alassafi M. The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review[J]. Computers and Education: Artificial Intelligence, 2024, 6: 100231.

[22] De Vreugd L, Van Leeuwen A, Jansen R, et al. Learning Analytics Dashboard Design and Evaluation to Support Student Self-Regulation of Study Behaviour[J]. Journal of Learning Analytics, 2024, 11(3): 249-262.