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Effect evaluation of blended teaching mode of biochemistry based on fuzzy information or methods

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SUMMARY: *In order to evaluate the effect of biochemistry blended teaching mode under the condition of uncertain teaching interaction, this paper proposed a fuzzy information computing framework that integrated teaching content mapping, online and offline behavior and multi-index effect judgment. This paper constructed a course dataset containing 186 undergraduates, 14 teaching weeks, 12,640 interaction records, 2,232 test responses, 744 experimental examination records and 368 discussion texts from the learning platform, classroom records and experimental teaching system. The fuzzy learning state is represented by membership coding, and a weighted fuzzy inference engine is designed to model knowledge participation, experiment completion, response timeliness and concept transfer. The evaluation model generates composite effect scores and category labels for different teaching stages. Experimental results show that the classification accuracy of this method is 96.8%, and the Macro-F1 value is 95.9%, which is 7.4 percentage points higher than that of the traditional weighted scoring method. The framework supports data-driven blended teaching evaluation in biochemistry and provides a computable basis for adaptive teaching adjustment, which remains stable across week outputs.*

KEYWORDS: *Fuzzy information processing; Teaching behavior modeling; Blended teaching evaluation; Intelligent computing*

1 Introduction

Biochemistry course has the characteristics of abstract concept, long reaction chain, intensive experimental operation and high requirements for knowledge transfer. It is difficult to fully present the continuous connection between metabolic regulation, molecular recognition and experimental inference in a single classroom teaching. Blended teaching organizes online resource browsing, classroom discussion, experimental training and stage tests in the same link, which provides conditions for fine-grained records of teaching process, and makes it possible for teaching effect evaluation to shift from experience judgment to data support. In this scenario, learning engagement, answer quality, experiment completion and classroom interaction frequency often have fuzzy boundaries, and directly adopting rigid thresholds is easy to compress the real differences. The fuzzy information processing method was introduced into the biochemistry blended teaching evaluation, which could map the teaching signals that were not completely consistent, gradual change of strength and stage fluctuation into computable features, and then combine data mining and intelligent analysis technology to complete the effect recognition. This path was more in line with the requirements of technical

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journals for educational computing research. The platform log, experimental image annotation, answer delay and discussion text semantics can be cleaned, aligned and fused under a unified data interface to form a stable input. This representation is conducive to subsequent classification, aggregation and comparative analysis, and reduces noise interference.

In recent years, foreign studies have begun to incorporate blended teaching activities of biochemistry and similar courses into the quantitative analysis framework. Zhao et al. [1] studied the random comparison process of online and offline integrated teaching in medicinal chemistry course, and proposed that the data-driven course organization method could link platform access, classroom participation and test results to observe the learning changes after teaching implementation. Lee et al. [2] studied the design of blended learning support materials for the topics of electron transport chain and oxidative phosphorylation in biochemistry courses, and proposed that pre-class and after-class digital aid could improve the segmented absorption of complex mechanism content. Harris et al. [3] studied the understanding level of biochemistry in the flipped classroom environment, and proposed to establish a structured observation index around the learning understanding degree, which was beneficial to describe students' mastery status of abstract content. Sun et al. [4] studied the combination of flipped classroom and virtual simulation platform in clinical biochemistry practice course, and proposed that digital preview before experiment and feedback after experiment could enhance the coherence of operation chain. Feng et al. [5] studied the online flipped classroom and team learning mode in the clinical experimental immunology course, and proposed that collaborative task arrangement could enhance the activity of teaching activities and the stability of results. Shen et al. [6] studied the combination path of improved team learning and flipped teaching in basic medical experimental courses, and proposed that the process participation and result performance should be included in the evaluation to better reflect the classroom operation state.

The above studies show that the blended teaching of biochemistry and similar courses has entered the stage of behavior modeling from resource stacking, but the evaluation variables are still mainly scores and questionnaires, which are difficult to completely deal with state gradual change and performance uncertainty. For comparison purposes, Table 1 summarizes the related studies.

Table 1: Summary of related studies

References	Research Object	Main Method or Conclusion
[1]	Integrated teaching of medicinal chemistry	Data-driven comparison of teaching implementation effects
[2]	Learning of key mechanisms in biochemistry	Construction of digital support materials for pre-class and post-class learning
[3]	Biochemistry understanding in the flipped classroom	Evaluation of understanding states through structured indicators
[4]	Practical teaching of clinical biochemistry	Integration of virtual simulation and flipped classroom
[5]	Teaching of clinical laboratory immunology	Team-based learning enhances activity participation
[6]	Basic medical experimental courses	Joint evaluation of process performance and outcome performance
[7]	Training strategies in clinical biochemistry	Student-centered training improves classroom effectiveness
[8]	Experimental teaching of molecular biology	Flipped classroom combined with improved team-based learning
[9]	Online-offline flipped teaching in the post-pandemic period	Verification of the feasibility of blended teaching
[10]	Teaching of industrial bioprocesses	Gamified virtual environments support teaching evaluation
[11]	Blended course of organic chemistry experiments	Construction of a competency evaluation system

In a more detailed evaluation dimension, Xu et al. [7] studied the student-centered experimental training strategy in clinical biochemistry teaching, and proposed that the training effect should be investigated from both experimental performance and learning experience. Qu et al. [8] studied the combination of flipped classroom and improved team learning in the experimental teaching of molecular biology, and proposed that the blended teaching evaluation needs to connect the three stages of pre-class preparation, classroom collaboration and experimental output. Wang et al. [9] studied the teaching effect of online and offline flipped classroom mode in the post-epidemic period, and proposed that the feasibility analysis should not stay at the level of summative scores, but also combine the implementation process data. Cotoras et al. [10] studied the virtual escape room game environment in the teaching of industrial biological processes, and proposed that interaction trajectories and task completion paths could be used as supplementary evidence for teaching evaluation. Ying et al. [11] studied the ability evaluation system in the organic chemistry experiment mixed course, and proposed that the consistency and traceability of evaluation could be improved by embedding the course ability indicators into the digital teaching process.

The existing research provides an empirical basis for the digital expression of blended teaching in biochemistry, and also shows a feasible direction to computerize, structure and model teaching activities. Based on this, this paper constructed an effect evaluation framework for blended teaching of biochemistry from the perspective of fuzzy information processing. The course resource access, in-class test, experimental operation record, discussion text and stage performance were uniformly encoded into multi-dimensional features, and the membership degree was used to describe the continuous change of learning state, and then fuzzy reasoning and weighted aggregation were used to determine the teaching effect. The design not only maintains the subject characteristics of biochemistry course content, but also strengthens the core role of computer method in teaching evaluation, which lays the foundation for subsequent model construction, data collection and experimental analysis.

2 Blended teaching mode of biochemistry based on fuzzy information or methods

2.1 The content organization and task stratification of biochemistry teaching under fuzzy information representation

The content organization in blended teaching of biochemistry is not a simple concatenation of online resources and offline experiments, but a mapping of knowledge points, task types and learning states into computable structures. There are obvious sequence dependence and difficulty differences among enzyme kinetics, metabolic pathway, molecular recognition and experimental operation. If the teaching is still advanced in a unified order, the deviation between teaching rhythm and learning acceptance is easy to occur. Lin et al. [12] studied the online and offline integrated teaching of process simulation courses, and proposed that content configuration should be coordinated with teaching links. Feng et al. [13] studied the multi-modal digital teaching quality evaluation model, and proposed that fuzzy BP neural network could deal with the uncertainty in heterogeneous teaching signals. Li et al. [14] studied the evaluation method of classroom learning effect, and proposed that the hierarchical mapping of behavior data can enhance the state discrimination ability. Based on this idea, the knowledge organization process is transformed into a computational process of "unit segmentation, fuzzy labeling, hierarchical mapping, task generation".

In order to describe the organizational strength of knowledge units in the current teaching stage, this paper first defines the knowledge weight calculation formula:

$$W_i = \frac{\mu_i(1 + d_i)\ln(1 + r_i)}{\sum_{k=1}^{N} \mu_k (1 + d_k)\ln(1 + r_k)} \quad (1)$$

Here, W_i represents the organizational weight of the i knowledge unit, μ_i represents the degree of mastery membership, d_i represents the strength of prior knowledge dependence, r_i represents the density of learning records, and N represents the total number of knowledge units. This formula takes knowledge status, structure dependence and behavior feedback into the same evaluation scale, which is used to determine the entry order and presentation proportion of content.

Fig. 1 shows the process of changing the teaching content from static chapters to dynamic task units. In the system, protein structure, enzymatic reaction, metabolic regulation and experimental specification were decomposed into minimal teaching units, and then the connection relationship was constructed according to concept association, experiment dependence and cognitive span. Then, the data such as preview duration, classroom answers, experiment submission and discussion text were read, and fuzzy labels such as "mastered", "partially mastered" and "to be strengthened" were assigned to each unit. Finally, differentiated content packages are generated according to the weight sorting results. The function of this process is not only to complete the content segmentation, but also to rewrite the original linear chapter order into a sortable, composable and traceable teaching structure, so that the subsequent task scheduling has a clear data basis.

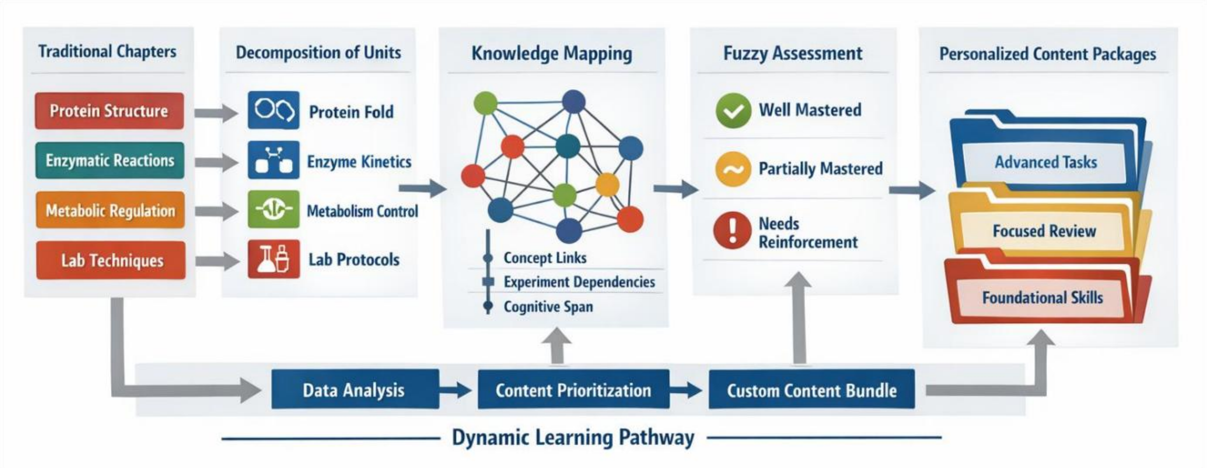

Figure 1: Fuzzy organization process of the biochemistry knowledge unit

In the task stratification stage, the system constructs a three-layer task structure according to knowledge weight and behavior response. The basic memory layer is used for term identification, structure memory and process reproduction. The mechanism understanding layer is used to explain reaction condition changes, regulatory relationships and experimental phenomena. The comprehensive application layer is used to complete case inference, metabolic pathway reconstruction, and abnormal result analysis. The three-layer task does not rely on a fixed threshold division, but dynamically matches according to the student state vector, so as to keep the task difficulty consistent with the learning readiness.

In order to describe the degree of adaptation between student states and task levels, this paper further constructs the matching score calculation formula:

$$S_{ij} = \alpha q_{ij} + \beta \min(\mu_{ij}^{a}, \mu_{ij}^{p}) + \gamma \exp\left(-\frac{|t_j - \tau_i|}{\sigma}\right) \tag{2}$$

Among them, S_{ij} represents the matching score between student j and task layer i, q_{ij} represents the degree of knowledge requirement conformity, μ_{ij}^{a} represents the membership degree of learning activity, μ_{ij}^{p} represents the membership degree of prior preparation, t_j represents the recent learning response time, τ_i represents the reference time of task layer, σ represents the time series attenuation coefficient, α, β, γ are the normalized weights and the sum of the three is 1. This formula compreszes content requirements, activity performance and time response into a unified framework, which can be used to decide the level and priority of task push.

Fig. 2 illustrates how the tasks run after being layered. Firstly, the system received four kinds of inputs, including pre-class preview, classroom test, experiment record and discussion behavior, and regenerated learning state vector. Then, according to the degree of knowledge preparation, classroom participation performance and experiment completion, students were corresponding to three types of task layers: basic memorization, mechanism understanding or comprehensive application. After the task push is completed, the platform continues to collect feedback signals such as the answer accuracy rate, submission delay and experimental correction times, which are used to revise the next round of status labels. This process formed a closed-loop connection between content organization and task stratification, so that blended teaching no longer stayed at the resource overlay level, but entered the dynamic configuration process based on state recognition.

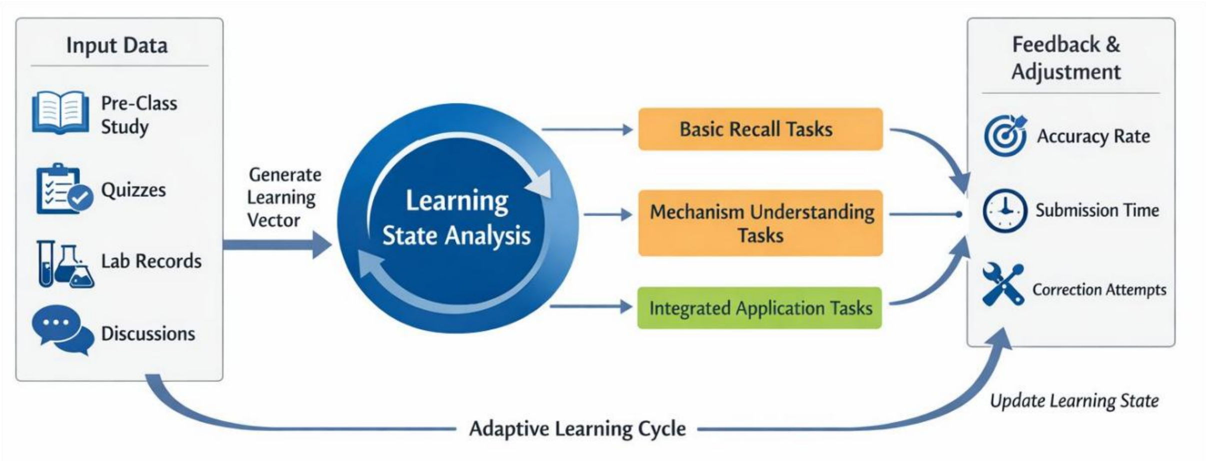

Figure 2: Task stratification and learning state mapping process

The organization of teaching content and the stratification of tasks under the fuzzy information representation are essentially the computational reorganization of the knowledge structure of biochemistry course. After knowledge unit, learning behavior and task difficulty are linked in the same data framework, teaching activities can make more detailed content arrangements according to state differences, and also provide input for subsequent teaching interaction adjustment and effect evaluation models.

2.2 The implementation mechanism of online and offline collaborative biochemistry blended teaching

The implementation mechanism of online and offline collaborative biochemistry blended teaching is a process that organizes platform learning, classroom explanation, experimental operation and feedback correction into a unified operation of the main link. The mechanism does not regard the online part as an auxiliary link of offline teaching, but realizes bidirectional linkage through data interface, status marking and task scheduling. Knowledge pre-activation and basic identification were undertaken before class; key explanation, structure deduction and interactive verification were undertaken in class; operation verification and result interpretation were undertaken in experiment; feedback archiving and task back-pushing were undertaken after class. Gong et al. studied the data-driven evaluation framework of teaching effect, and proposed that fuzzy comprehensive analysis could transform multi-source teaching signals into stable evaluation basis [15]. Mei studied the quality assurance model of higher education based on fuzzy neural network, and proposed that the introduction of fuzzy mapping and network learning mechanism in complex education scenarios is beneficial to enhance the adaptation ability of the evaluation system [16]. Ouhaichi et al. studied the development trend of multimodal learning analysis and proposed the joint modeling of platform logs, classroom behaviors and interactive data, which could more completely present the running state of teaching activities [17].

Fig. 3 presents the main process of the collaborative implementation architecture. The system first receives the preview time, video stay, test answer and resource access records from the learning platform, and then collects the in-class Q&A, interactive feedback and stage quiz results from the classroom. At the same time, the system accesses the operation steps, result submission and error correction records of the experimental end. After the three types of data are aligned on the unified timeline, they are sent to the teaching state fusion module to generate the comprehensive state vector of knowledge readiness, classroom responsiveness and experiment completion. Then, the scheduling module allocated the depth of explanation, the intensity of experimental prompts, and the type of after-class exercises according to the status results, so that the online input and the offline implementation formed a continuous connection.

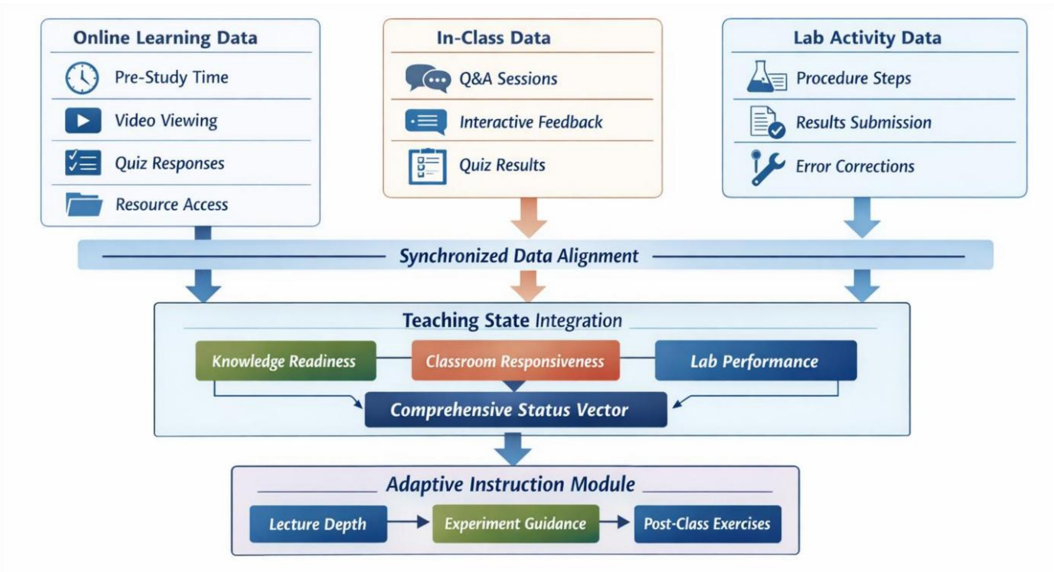

Figure 3: The implementation architecture of biochemistry teaching with online and offline collaboration

In order to characterize the collaborative contribution of each teaching stage, this paper constructs the stage coupling strength calculation formula as follows:

$$C_j = \frac{\sum_{m=1}^{M} \omega_m x_{jm} \mu_{jm}}{\sqrt{\sum_{m=1}^{M} (\omega_m x_{jm})^2 + \lambda}} \tag{3}$$

Here, C_j represents the collaborative contribution value of the j teaching stage, x_{jm} represents the response strength of the m observed feature in this stage, μ_{jm} represents the fuzzy membership degree of the corresponding feature, ω_m represents the feature weight, M represents the total number of features, and λ represents the smoothing term. This formula describes the stage effectiveness through the weighted response and membership degree product, and can be used to judge the difference in the role of pre-class, class and experiment links in the overall link.

Fig. 4 illustrates the task scheduling and feedback reflow process. The system first generated the classroom task package according to the pre-class status, and then generated the experimental task package according to the classroom response results. After the experiment, it continued to retrieve the source of error, the number of corrections and the quality of result interpretation, and wrote these information back to the student status file. After the status file was updated, the platform automatically revised the difficulty of the next round of preview materials and the exercise structure, so that the teaching implementation formed a closed loop.

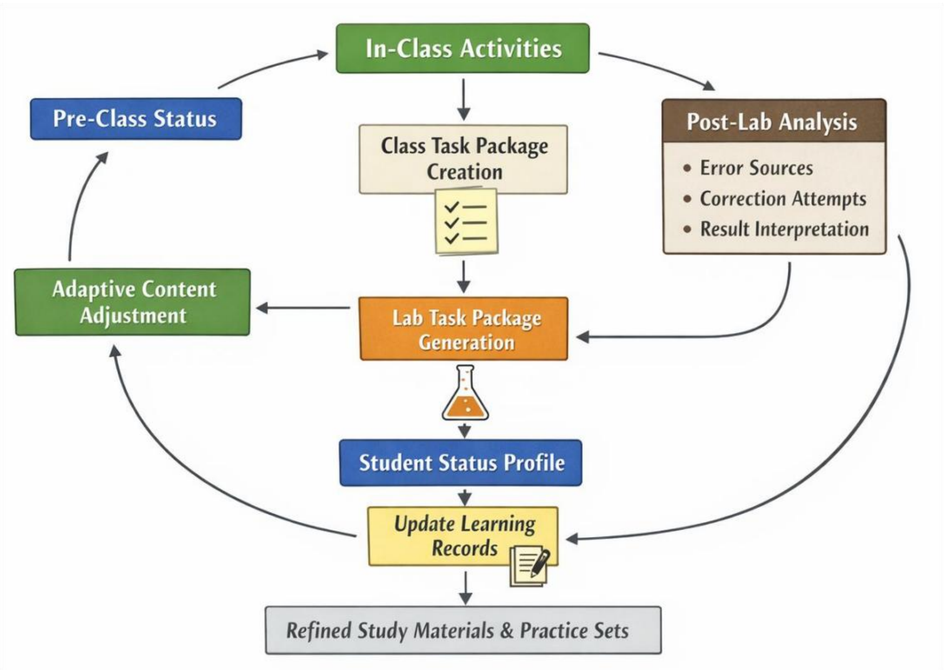

Figure 4: Teaching task scheduling and feedback reflux process

In order to realize the adaptive selection of task push, this paper further defines the task scheduling score:

$$R_{jn} = \eta_1 C_j + \eta_2 \frac{f_{jn}}{1 + e^{-g_{jn}}} + \eta_3 \left(1 - \frac{|p_n - \bar{p}_j|}{\bar{p}_j + \epsilon}\right) \tag{4}$$

Here, R_{jn} represents the scheduling score of task n in teaching stage j, f_{jn} represents the matching strength between task content and current knowledge unit, g_{jn} represents the behavior feedback gain, p_n represents the expected load of task, $\bar{p}_j$ represents the average load that can be carried in stage, ϵ represents a small constant, and η_1, η_2, and η_3 are normalized weights. This formula takes into account stage state, content matching and load constraint, and can be used to complete differentiated task allocation.

The implementation mechanism of online and offline collaborative biochemistry teaching is essentially to integrate multi-source teaching activities into a unified scheduling system. After the integration of platform data, classroom behaviors and experimental records in the same framework, teaching activities can be continuously adjusted according to state changes, thus providing stable input for subsequent interactive adjustment and effect evaluation. The mechanism can also retain stage logs, status labels and task execution traces in the teaching server, which is convenient for subsequent horizontal comparison, vertical tracking and model parameter update. It makes the implementation process computable, traceable and reusable, and provides consistent data interface and analysis basis guarantee for curriculum iteration.

2.3 Teaching interaction adjustment and learning state judgment based on fuzzy method

The teaching interaction adjustment based on fuzzy method is not a static record of classroom behaviors, but organizes online access, classroom response, experimental operation and feedback correction into a continuously updated state chain. In hybrid biochemistry teaching, students' responses to metabolic pathways, enzyme kinetics, structure recognition and experimental steps do not present absolutely clear boundaries, and the single answer results are difficult to completely reflect the real state. Therefore, it is necessary to transform multi-source interaction behaviors into computable fuzzy states. Banihashem et al. studied the role of learning analytics in the feedback practice of higher education and proposed that the feedback mechanism should be based on interpretable data evidence [18]. Alfredo et al. studied human-centered learning analysis and artificial intelligence application in education, and proposed that state recognition should take into account both behavioral characteristics and learning experience [19]. Sailer et al. studied the analysis framework of closed-loop learning and proposed that a circular connection relationship should be formed among teaching activities, learning response and feedback update [20]. Based on the above research, this section divides the teaching interaction regulation into five continuous links: interaction sampling, state mapping, comprehensive judgment, transition identification and regulation execution.

In order to describe the cumulative effect of teaching interaction in a continuous time window, this paper first defines the time series fusion expression of interaction strength. Behaviors such as online video stay, resource access, classroom question and answer, experimental correction and assignment submission have different roles in the teaching stage, and the behaviors closer to the current time can reflect the immediate status of students, so it is necessary to add a attenuation mechanism in the time dimension. The comprehensive interaction strength is defined as follows.

$$I_t = \sum_{u=1}^{U} \rho_u \, c_{tu} \left(\frac{1}{L} \sum_{\tau=t-L+1}^{t} x_{\tau u} \, e^{-\lambda(t-\tau)} \right) \tag{5}$$

Here, I_t represents the comprehensive interaction strength in the t time window, $x_{\tau u}$

represents the observed value of the uth type of interaction behavior at time point τ, ρ_u represents the global weight of this type of behavior, c_{tu} represents the confidence coefficient of the behavior in the current time window, L represents the length of the sliding window, λ represents the time decay parameter, and U represents the total number of interactions. This formula uniformly compressed the multi-source discrete behaviors into continuous intensity values, so that the pre-class preview, in-class response and after-class revision could enter the subsequent judgment process under the same scale.

After the interaction strength is formed, it is also necessary to convert the numerical states into fuzzy membership degrees to describe the possibility of students in different learning states. Because the learning status in biochemistry course is often determined by multiple variables, a single linear mapping is difficult to reflect the correlation between features. This paper uses the normalized fuzzy mapping function with covariance constraint:

$$\mu_t^{(h)} = \frac{\exp\left[-\frac{1}{2}(v_t - m_h)^T \Sigma_h^{-1} (v_t - m_h)\right]}{\sum_{g=1}^{H} \exp\left[-\frac{1}{2}(v_t - m_g)^T \Sigma_g^{-1} (v_t - m_g)\right]} \tag{6}$$

where $\mu_t^{(h)}$ represents the membership degree of time window t belonging to the h learning state, v_t represents the state feature vector composed of interaction strength, answer performance, experimental results and text semantics, m_h represents the state center of the h class, Σ_h represents the corresponding covariance matrix, and H represents the number of state categories. The formula can continuously express the gradual states such as "low response", "medium response", "high response", "stable grasp", "local fluctuation" and "need to be strengthened", so as to avoid the compression of real learning differences by rigid classification.

After the fuzzy membership degree is obtained, the system needs to further generate a unified learning state score to support teaching adjustment. Blended biochemistry teaching not only includes knowledge understanding, but also includes experiment execution and text feedback, so the state judgment cannot only rely on the interaction behavior itself. To this end, this paper constructs the cross-modal learning state score calculation formula as follows:

$$Z_t = \theta_1 \sum_{h=1}^{H} \omega_h \mu_t^{(h)} + \theta_2 k_t + \theta_3 e_t + \theta_4 \tanh(r_t^T P s_t) \tag{7}$$

Here, Z_t represents the comprehensive learning state score of time window t, ω_h represents the contribution weight of class h state, k_t represents the degree of knowledge mastery, e_t represents the consistency of experiment execution, r_t represents the classroom response vector, s_t represents the semantic vector of discussion text or written feedback, P represents the cross-modal mapping matrix, and θ_1 to θ_4 are the normalized fusion parameters. This formula puts behavior, experiment and semantic feedback into the same evaluation framework, so that the learning state can reflect the changes in theoretical understanding, experimental quality and language expression at the same time.

After completing the state scoring, the teaching system also needs to determine whether the current state is stable maintenance, short-term fluctuation, or continuous decline. If we only compare the current value with the previous moment, it is easy to be affected by the sporadic behavior. Therefore, this paper introduces the local mean and historical fluctuation constraints to construct the learning state transition increment function:

$$\Delta_t = Z_t - \left[\phi_1 Z_{t-1} + \phi_2\left(\frac{1}{W}\sum_{\tau=t-W}^{t-1} Z_\tau\right) + \phi_3\sqrt{\frac{1}{W}\sum_{\tau=t-W}^{t-1}(Z_\tau - \bar{Z}_t)^2}\right] \tag{8}$$

where Δ_t represents the offset of the current time window from the baseline of the historical state, Z_{t-1} represents the state score at the previous time, W represents the length of the historical window, $\bar{Z}_t$ represents the mean value of the state within the window, ϕ_1, ϕ_2, ϕ_3 represent the weights of history inheritance, local mean, and volatility penalty, respectively. This formula can suppress the misjudgment caused by short-term outliers while retaining the current response information, so as to identify the change direction of the stage state more stably.

After obtaining the state offset, the system needs to convert the decision results into executable adjustment actions. The higher the intensity of teaching adjustment is not better, and the balance relationship between knowledge gap, behavioral fluctuation, task load and current participation level should also be considered. Based on this, this paper defines the adaptive adjustment intensity function with load constraint:

$$A_t = \frac{1}{1 + \exp\left[-\left(\eta_1\Delta_t + \eta_2 q_t + \eta_3 b_t - \eta_4\frac{|l_t - \bar{l}|}{\bar{l} + \varepsilon}\right)\right]} \cdot \left(1 - \frac{1}{1 + \exp[-\xi(\bar{p} - p_t)]}\right) \tag{9}$$

Here, A_t represents the teaching adjustment intensity of time window t, q_t represents the knowledge mastery gap, b_t represents the amplitude of behavior fluctuation,l_t represents the current task load, $\bar{l}$ represents the average loadable load, ε represents the tiny constant to prevent the denominator from being zero, p_t represents the current participation level, $\bar{p}$ represents the target participation level, η_1 to η_4 and ξ are the adjustment parameters. When the current value is large, the system will increase the prompt information, shorten the task span, strengthen the experimental demonstration or supplement the basic resources. When the current value is small, the original rhythm is maintained or only a light correction is made. This can avoid the output of too strong intervention when the task load is too high or the participation is insufficient, and make the adjustment process more stable.

The computational chain formed by Equations (5) to (9) transforms the instructional interaction regulation from empirical judgment into a continuous process that can be sampled, mapped, tracked and updated. After online platform logs, classroom interaction records, experimental trajectories and feedback texts are integrated in a unified framework, the system can continuously generate student state portraits, and adjust the depth of explanation, the intensity of experimental prompts and the hierarchical path of tasks accordingly. The mechanism not only retains the discipline characteristics of complex knowledge structure and close experiment correlation of biochemistry course, but also highlights the core role of computer method in state recognition, dynamic adjustment and closed-loop update, which provides a stable, traceability and time-series input basis for subsequent teaching effect evaluation models.

3 Evaluation model of biochemistry blended teaching effect based on fuzzy method

The blended teaching effect evaluation model of biochemistry based on fuzzy method takes the unified coding of multi-source teaching behaviors as the premise, fuzzy state mapping and hierarchical aggregation calculation as the core, and outputs the stage effect value, category label and change trend after the implementation of the course. The model does not take the grade as the only result, but integrates the pre-class preview, classroom response, experiment execution, discussion text and after-class correction into the evaluation chain at the same time, so that the knowledge mastery, experimental understanding and interactive participation in the course of biochemistry can be completed in the same framework. The main process of "data access, feature mapping, fuzzy reasoning, effect aggregation and result writing back" was adopted in the system implementation of the model. The platform was responsible for log collection and data cleaning, the computing end was responsible for state determination and parameter update, and the teacher end was responsible for reviewing the evaluation results and performing subsequent adjustment.

The model shown in Fig. 5 consists of five parts. The data access layer receives learning platform logs, classroom tests, experiment records and discussion texts. The feature representation layer completes numerical normalization, semantic vectorization and time alignment. The fuzzy reasoning layer generates multi-class membership degrees according to state rules. The effect evaluation layer outputs the total score, hierarchical label and stage fluctuation value. The result feedback layer writes the evaluation results back to the course database, which is used to support the next round of task configuration. Such a model structure not only maintains the time continuity of teaching data, but also enhances the traceability of the evaluation process.

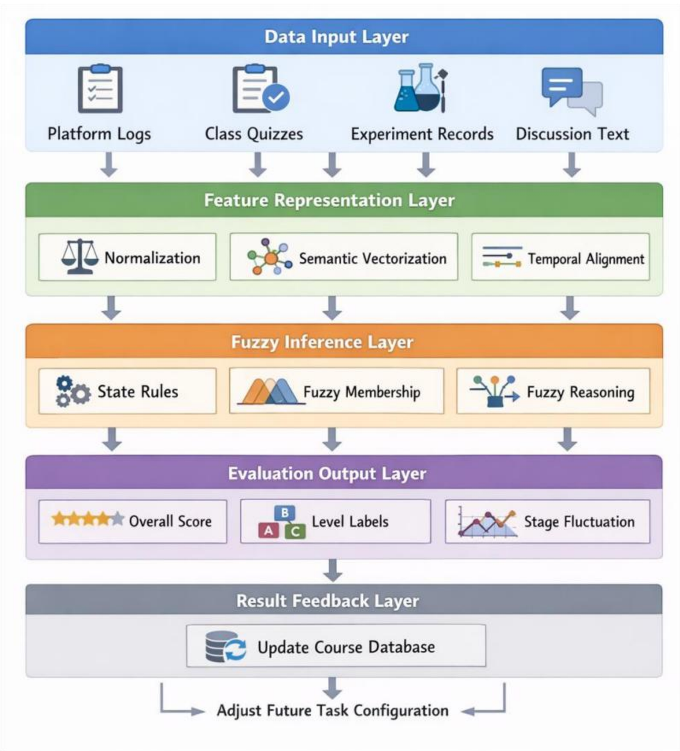

Figure 5: Structure of evaluation model for blended teaching effect of biochemistry based on fuzzy method

To ensure that each modal feature maintains a consistent scale at the input, the sample fusion vector is defined as follows.

$$x_t = [\gamma_1 p_t \parallel \gamma_2 c_t \parallel \gamma_3 e_t \parallel \gamma_4 s_t] \tag{10}$$

Here, x_t represents the unified sample vector of the t time window, $\parallel$ represents the feature splicing operator, p_t, c_t, e_t and s_t represent the sub-vectors of pre-class learning, classroom interaction, experiment execution and text semantics, respectively, and γ_1 to γ_4 represent the modal gating coefficients. This formula collects the behavior records originally scattered in different systems into the same input plane, and provides the basis for subsequent fuzzy reasoning.

The direct participation of a single feature in the calculation is easy to amplify the noise, so the model further weights the feature reliability. The feature weight update is defined as follows.

$$\omega_m^{(t)} = \frac{\exp\left(\alpha r_m^{(t)} - \beta v_m^{(t)}\right)}{\sum_{j=1}^{M} \exp\left(\alpha r_j^{(t)} - \beta v_j^{(t)}\right)} \tag{11}$$

Here, $\omega_m^{(t)}$ represents the effective weight of the m class feature in the t round calculation, $r_m^{(t)}$ represents the correlation strength between the feature and the stage label, $v_m^{(t)}$ represents the volatility of the feature in adjacent time Windows, α and β represent the smoothing parameters, and M represents the total number of features. This formula makes the features with strong correlation and small fluctuation obtain higher weights, thereby reducing the interference of outliers on the evaluation results.

In the fuzzy inference layer, the system maps each student sample onto a number of teaching state rules. In order to express the activation strength of the r-th rule on the t-th sample, this paper gives the rule trigger function:

$$\alpha_r^{(t)} = \prod_{d \in \mathcal{D}_r} \left(\mu_{rd}(x_{td})\right)^{\zeta_{rd}} \tag{12}$$

where $\alpha_r^{(t)}$ represents the activation value of the r fuzzy rule, $\mathcal{D}_r$ Represents the set of variable dimensions involved in the rule, $\mu_{rd}(x_{td})$ represents the membership function value of the d dimension in the rule, ζ_{rd} represents the dimension importance coefficient. The continuous multiplication structure can retain the synergistic effect of each dimension when it is satisfied together, and distinguish the combination state of "sufficient preview but weak experiment" and "active class and accurate expression".

After the rule activation is completed, the model needs to form the stage effect score. The course is divided into four evaluation stages: pre-class, in-class, experimental and post-class, and the stage effect score is written as follows.

$$E_s = \frac{\sum_{r=1}^{R} \beta_{sr}\, \alpha_r^{(t)}}{\sum_{r=1}^{R} \beta_{sr}} + \kappa h_s \tag{13}$$

Here, E_s represents the effect score of the s stage, β_{sr} represents the contribution weight of the r rule to this stage, R represents the total number of rules, $\alpha_r^{(t)}$ represents the activation strength of the sample under the rule, h_s represents the teacher check item, and κ

represents the manual check coefficient. The formula combines the automatic reasoning results with the manual verification information, so that the model not only maintains the consistency of calculation, but also retains the professional judgment in the teaching scene.

In order to obtain the overall effect evaluation at the course level, this paper introduces temporal smoothing and trend correction on the basis of stage score, and the comprehensive score is defined as follows.

$$Y = \sum_{s=1}^{S} \lambda_s E_s + \sum_{s=2}^{S} \tau_s (E_s - E_{s-1}) e^{-\delta(S-s)} \tag{14}$$

Here, Y represents the overall effect value of the course, λ_s represents the stage weight, τ_s represents the trend gain coefficient between stages, δ represents the time decay factor, and S represents the total number of stages. This formula can integrate the performance of different stages into the unified evaluation space, and give a higher response to the continuous improvement of the learning trajectory, so it is more suitable for the overall evaluation in the blended teaching environment.

The model needs to be trained with both classification accuracy and rating consistency in mind, so the objective function is written as follows.

$$\mathcal{L} = \theta_1 \mathcal{L}_{cls} + \theta_2 \mathcal{L}_{reg} + \theta_3 ||W||_2^2 \tag{15}$$

Here $\mathcal{L}$ represents the overall training loss, $\mathcal{L}_{cls}$ represents the classification loss, $\mathcal{L}_{reg}$ represents the score regression loss, $||W||_2^2$ represents the parametric regularization term, and θ_1, θ_2, and θ_3 represent the balancing coefficients. On the one hand, this formula constrict the classification error of the evaluation label, on the other hand, it controls the deviation between the continuous score and the true observation, and keeps the parameter stable by regularization. After training, the system uses the training set to update the parameters, and then outputs the stage effect value, level label and fluctuation trend on the validation set and the test set.

After completing the input representation, feature weighting, rule activation, stage aggregation, overall score and objective function definition, the main evaluation variables in the model can be further summarized into the five-category structure shown in Table 2. This table is used to illustrate the position and role of different variables in the calculation chain of effect evaluation, so as to facilitate the interpretation of indicators and comparison of results in subsequent experiments.

Table 2: Evaluation variables and their computational roles

Variable Group	Constituent Content	Computational Role
Pre-class Preparation Variables	Preview duration, video completion rate, resource access depth	Describe the preparation state before knowledge acquisition
Classroom Interaction Variables	In-class responses, question-answer reactions, blackboard-following degree	Describe immediate understanding and participation intensity
Experimental Execution Variables	Step completion rate, number of error corrections, result consistency	Describe operational understanding and experimental quality
Text Feedback Variables	Discussion semantics, reflection completeness, terminology usage accuracy	Describe the level of conceptual expression and transfer
Temporal Stability Variables	Periodic fluctuation, delay variation, continuous improvement range	Describe the stability of performance across stages

In Table 2, the pre-class preparation variable is used to describe the degree of preparation before knowledge entry, the classroom interaction variable is used to reflect the immediate absorption and participation intensity, the experiment execution variable is used to represent the operation understanding and the experiment completion quality, the text feedback variable is used to supplement the concept expression and transfer level, and the time series stability variable is used to describe the continuity and fluctuation characteristics of stage performance. In this way, the multi-source teaching signals in the model can correspond to the subsequent experimental indicators and result analysis in a clearer structure.

The model output consists of three levels. The first layer is the stage effect value, which is used to reflect the specific state of preparation before class, classroom absorption, experimental understanding and revision after class. The second layer was the grade label, which was used to distinguish four types of teaching effects: excellent, good, medium and to be strengthened. The third layer is the trend vector, which is used to describe the rising, stable and fluctuating states of students in consecutive teaching weeks. The three types of results together form the course evaluation output, so that the teacher can not only view the overall score, but also locate the source of change in specific links.

In the system deployment, the training data set is responsible for parameter learning, the validation data set is responsible for adjusting the weights and thresholds, and the test data set is used to test the generalization performance of the model. When the evaluation results reach the set accuracy, the platform solidifies the current model as a service interface, and receives new data for incremental update in the subsequent teaching cycle. In this way, the fuzzy evaluation model can not only judge a single round of teaching, but also make a horizontal comparison of the implementation effect between different classes, different chapters and different experimental projects. The model server also keeps the rule trigger log, phase weight snapshot and teacher revision record, which is convenient for subsequent audit, reproduction of experimental results and completion of cross-semester migration.

4 Experimental data collection

4.1 Data collection and preprocessing process of teaching process

The data collection and preprocessing process of teaching process includes obtaining the whole process data formed by biochemistry blended teaching on the platform end, the classroom end and the experimental end. These data are used as sample data sets to construct the teaching effect evaluation model based on fuzzy method and analyze the key variables that affect the quality of curriculum implementation. Data were collected from 186 undergraduate students in the same biochemistry course, and the collection period was 14 teaching weeks. The platform recorded students' pre-class preview video stay, page access depth, resource download, chapter test submission and after-class review behavior. In the classroom, the Q&A, instant quiz, interactive feedback and check-in information were recorded. At the experimental end, the completion of the experimental steps, the result submission time, the number of error corrections and the text content of the report were recorded.

A total of 12640 interactive records, 2232 test responses, 744 experimental assessment records and 368 discussion texts were collected to describe the learning preparation, classroom response and experimental performance in the course implementation process. The course management platform is responsible for collecting students 'basic information and learning logs, including student number, class, grouping, task completion time and score status. The classroom collection module is responsible for saving the in-class answer, question response and stage test information. The experimental teaching system is responsible for recording the experiment number, step achievement rate, instrument operation results and experiment report content.

In order to ensure the stability of subsequent model training, anonymization, missing value imputation, abnormal record elimination, timestamp alignment and feature standardization are performed on the original data after entering the database. Text data were segmented and term cleaning were used to remove invalid expressions, behavioral data were aggregated according to a uniform time window, and experimental data were recoded according to the operation order and result consistency. After preprocessing, the data from different sources are mapped into a unified structure to form a standardized data set that can be used for fuzzy state recognition, stage score calculation and result comparison analysis.

In the process of data sorting, all records were indexed according to week, chapter and experimental project, and then multi-table association was completed according to student number to avoid mismatch between platform logs, classroom records and experimental results. Min-max normalization is used for continuous indicators, label coding is used for discrete indicators, and text semantic features are represented by vectors and concatenated with numerical features to form a unified input matrix. The processed data were divided into four subsets: pre-class preparation, classroom interaction, experiment execution and after-class feedback, and were written to the analysis server synchronously for the subsequent construction of training set, validation set and test set. All acquisition nodes adopt uniform field naming and verification rules, duplicate records are merged according to priority, and inconsistent data are converted according to preset templates, so as to ensure clear input boundaries, traceability of data sources and consistency of the overall structure.

4.2 Sample selection criteria and construction of evaluation variables

The sample selection criteria and evaluation variables construction are based on the data set that has been cleaned and standardized. The core task is to determine the effective samples to enter the model training, and reassemble the original teaching records into computable evaluation variables. The sample screening was carried out with students as the main index, teaching weeks as the timeline, and chapter tasks and experimental projects as observation nodes. The included samples should meet the three requirements of complete course participation chain, consistent identity across systems, and continuous tracking of key behaviors, that is, a stable mapping can be formed between pre-class learning, in-class tests, experiment submission and after-class feedback. Samples with only single-ended records, too large stage gaps, disordered time order, or unable to complete the primary key association are not included in the subsequent modeling. After the screening, the evaluation variables were further constructed around the five dimensions of knowledge preparation, classroom response, experimental performance, semantic expression and time series change, and a unified feature matrix was formed through coding, compression and screening for subsequent fuzzy reasoning, stage scoring and result comparison analysis.

In the sample division stage, the reserved samples were randomly shuffled according to the student number and divided into training set, validation set and test set according to the stratified sampling method. At the same time, the distribution proportion of different weeks, different chapters and different experimental items is kept consistent in the division process, so as to avoid too dense samples in a certain teaching stage and affect the model learning. The training set is used for parameter updating, the validation set is used for weight adjustment and threshold calibration, and the test set is used to test the generalization performance of the model. The sample index in the computing environment is generated by the database, and the cross-table matching is completed by the uniform primary key.

The evaluation variables were constructed from five dimensions: pre-class preparation, classroom interaction, experiment execution, text feedback and time series stability. The pre-class preparation variables included preview duration, video completion rate and resource access depth. The classroom interaction variables included the correct rate of answering in class, the response frequency of question answering and the real-time feedback delay. The execution variables included step completion rate, error correction times and result consistency. The text feedback variables include term coverage, reflective integrity and semantic similarity. Time-series stable variables include intra-week volatility magnitude, stage improvement rate, and continuous participation. After normalization or coding, all variables are written into a unified feature matrix, which is retained and compressed according to the relevance and interpretability, so as to form a standardized input set suitable for fuzzy reasoning, effect scoring and comparative analysis.

5 Experimental Results

5.1 Analysis of model evaluation results

After dividing the training set, validation set and test set, this paper first checks the output state of the established fuzzy evaluation model. The model input consisted of five types of features: pre-class preparation, classroom interaction, experiment execution, text feedback and time series stability, and the output was stage effect value, comprehensive score and grade label. In order to avoid the single average value covering the chapter differences, this paper re-aggregated the data of the 14 teaching weeks according to the four links of preview, class, experiment and feedback, and counted the response intensity of different links on each core index. The results showed that there was a high degree of synergy between pre-class preparation and classroom interaction, and a stable positive correlation between experimental execution and text feedback, indicating that knowledge understanding and operation completion in blended teaching of biochemistry were not isolated changes, but promoted synchronously in a continuous task chain. The overall classification accuracy of the model on the test set is 96.8%, Macro-F1 is 95.9%, and the Pearson correlation coefficient between the comprehensive score and the teacher's review results is 0.934, which shows that the model has good fitting ability on the two output links of category judgment and continuous scoring.

As shown in Fig. 6, there are obvious differences in the response intensities of the four types of teaching links in the five core indicators. The heat value of pre-class preparation on knowledge mastery was 0.81, indicating that the preview session had a strong supporting effect on the entry of basic knowledge. The heat value of classroom interaction on classroom responsiveness reached 0.91, which was the highest value of all indicators, indicating that instant question answering and in-class tests were the most direct to knowledge absorption. The heat value of experimental execution on experimental consistency was 0.93, indicating that the experimental process had significant support for the course effect. The heat values of after-class feedback on semantic expression and temporal stability were 0.88 and 0.84, respectively, indicating that reflection and revision were more conducive to consolidating expression and maintaining continuous improvement.

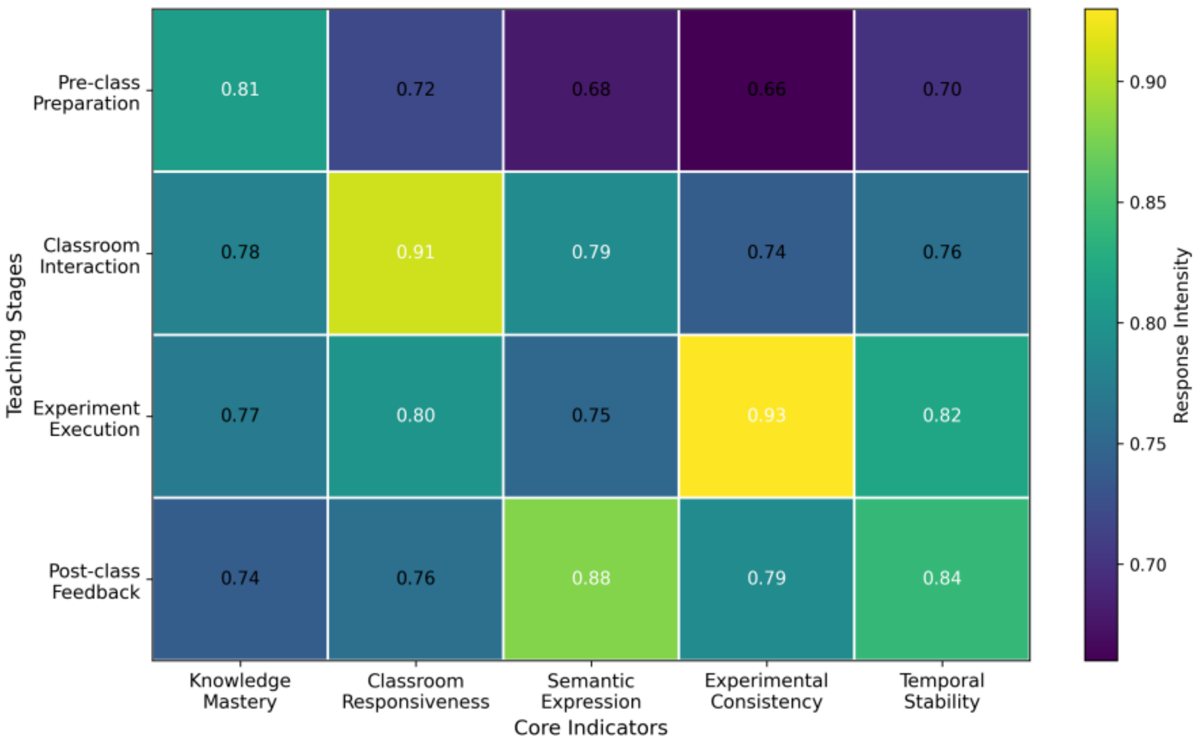

Figure 6: Heat map of response intensity between different teaching links and core indicators

In order to further test the consistency between the model output and the real performance of the course, this paper counted the mean differences of samples at different levels in the comprehensive rating, stage fluctuation value and teacher review score, and the results are shown in Table 3.

Table 3: Mean values of evaluation results for samples with different effect levels

Level	Overall Score	Classroom Responsiveness	Experimental Consistency	Semantic Expression	Teacher Review Score
High-Efficiency Group	0.934	0.912	0.941	0.903	93.8
Good Group	0.872	0.854	0.881	0.846	87.1
Intermediate Group	0.801	0.786	0.812	0.775	80.4
Group Requiring Reinforcement	0.694	0.663	0.708	0.641	69.2

As can be seen from Table 3, the comprehensive score difference between the efficient group and the group to be strengthened reaches 0.240, and the difference in the teacher's review score is 24.6 points, indicating that the model has strong discrimination between different teaching states. Further observation of the fluctuation results of the stage showed that the efficient group kept a steady rise within 14 weeks, the good group showed a slight fluctuation in the sixth and tenth weeks and then quickly stabilized, the intermediate group was mainly affected by the difficulty of the experimental task, and the group to be strengthened continued to be low in the two dimensions of pre-class preparation and classroom response. Combined with the results in Fig. 6, it can be seen that the low value areas identified by the model have a high degree of overlap with the weak links recorded in the teacher's review, indicating that the method can accurately locate the difference in the effect of biochemistry blended teaching, and provide a stable basis for subsequent comparison experiments.

5.2 Comparative Analysis

In order to test the effectiveness of the proposed model in overall performance, this paper selects weighted scoring method, support vector machine, random forest, MLP and fuzzy BP network as comparison methods, and uniformly uses accuracy, precision, recall and Macro-F1 as evaluation indicators. All models were run on the same training set, validation set and test set, the input features were consistent, and the parameters were adjusted by the validation set before the final results were output. The overall performance comparison results are shown in Table 4.

Table 4: Overall performance comparison of different methods

Model	Accuracy / %	Precision / %	Recall / %	Macro-F1 / %
Weighted Scoring Method	89.4	87.8	88.1	88.5
SVM	91.3	90.1	90.7	90.4
Random Forest	92.7	91.6	92.2	91.9
MLP	93.1	92.4	92.7	92.5
Fuzzy BP Network	93.6	94.1	93.4	92.7
Proposed Model	96.8	95.7	96.2	95.9

Table 4 shows that the proposed model maintains the highest level of accuracy and Macro-F1, and the accuracy reaches 96.8%, which is 7.4 percentage points higher than that of the traditional weighted scoring method and 3.2 percentage points higher than that of the fuzzy BP network. It shows that the evaluation chain based on fuzzy rules and multi-source feature aggregation can more fully retain the stage differences in biochemistry blended teaching. By further observing the precision and recall rate, it can be found that the proposed model has no obvious imbalance in the two indicators, indicating that the classification boundary is stable and there is no bias caused by the large number of one-class samples.

In order to analyze the contribution of each component of the model, the ablation experiments were continued, and the results are shown in Table 5.

Table 5: Results of ablation experiments

Model Configuration	Accuracy / %	Precision / %	Recall / %	Macro-F1 / %
Full Model	96.8	95.7	96.2	95.9
Without Semantic Feedback Branch	94.9	93.8	94.1	93.5
Without Experimental Consistency Constraint	95.1	94.6	93.7	94.0
Without Temporal Stability Term	95.4	94.9	94.5	94.3
Without Teacher Verification Term	95.8	95.0	95.1	94.9

Table 5 shows that the Macro-F1 of the model decreases most obviously after removing the semantic feedback branch, indicating that the discussion text and reflection expression have a direct supporting role in the judgment of teaching effect. After removing the experimental consistency constraint, the recall rate decreases greatly, which indicates that the experimental performance is an indispensable structural signal in the evaluation of biochemistry courses. After removing the time series stability term, although the accuracy decreases, the fluctuation increases more obviously, indicating that this term mainly affects the output stationarity of the model. On the whole, the performance advantage does not come from the superposition of single modules, but from the collaboration of content organization, interaction adjustment and timing correction.

In order to investigate the usability of the model in real teaching deployment, this paper also counts the performance of each method in single-round inference time, video memory occupancy and cross-week stability, and the results are shown in Table 6.

Table 6: Comparison of efficiency and stability of different methods

Model	Single-Round Inference Time / ms	Memory Usage / MB	Cross-Week Standard Deviation	Deployment Adaptability
Weighted Scoring Method	6.4	58	0.084	High
SVM	11.7	96	0.067	High
Random Forest	15.2	118	0.061	Medium
MLP	18.9	164	0.056	Medium
Fuzzy BP Network	21.3	173	0.051	Medium
Proposed Model	24.6	186	0.038	High

As can be seen from Table 6, although the computational complexity of the proposed model is higher than that of the weighted scoring method and support vector machine, the inference time is still controlled at the millisecond level and the cross-week standard deviation remains the lowest, indicating that the method has good deployment feasibility in the teaching platform environment. Compared with the fuzzy BP network, the proposed model is finer in the joint expression of experimental consistency and text semantics, so it can better distinguish the boundary between the good group and the middle group. Compared with random forest and MLP, the proposed model is less sensitive to cross-week fluctuations and still maintains stable output when the experimental task switches in the sixth and tenth weeks. This shows that the constructed fuzzy evaluation mechanism is not only suitable for static result judgment, but also suitable for dynamic effect analysis in continuous teaching weeks. From the deployment point of view, the model can not only output the total score, but also retain the stage label and trend vector, which is convenient for teachers to call and subsequent review.

6 Discussion

The discussion of this study is based on the model structure, sample construction and experimental results of the above, and does not isolate the evaluation index for isolated judgment. From the comparison results, although the implementation cost of the weighted scoring method is low, it is difficult to deal with the continuous change of the fuzzy state in the teaching process. Support vector machine and random forest can complete the classification task, but less retain the linkage relationship between experimental consistency, semantic expression and stage fluctuation in biochemistry course. MLP and fuzzy BP network have certain advantages in nonlinear fitting, but the structured expression of multi-source behavioral signals is still not fine enough, and the cross-week output is easily affected by local sample fluctuations. The model in this paper maintained good results in accuracy, Macro-F1 and cross-week standard deviation, indicating that the joint design of fuzzy rules, timing correction and teacher verification items was more suitable for describing the real effect changes in blended teaching. More importantly, the model not only outputs the total score, but also retains the results of four stages: pre-class preparation, classroom interaction, experiment execution and after-class feedback, so that the evaluation process changes from single point judgment to chain analysis. For the course of biochemistry, this calculation method is closer to the teaching characteristics of knowledge understanding, experimental verification and expression transfer, and also provides a more stable basis for subsequent chapter comparison, class comparison and teaching adjustment. At the same time, the consistency between the heat map and the group mean results is high, the low value area is mainly concentrated in the samples with insufficient preparation before class and weak classroom response, and the high efficiency group continues to lead in the experimental consistency and semantic expression. This shows that the model has good positioning ability and explanation ability.

7 Conclusions

Focusing on the evaluation task of biochemistry blended teaching effect based on fuzzy information or methods, this paper constructed a computational model consisting of multi-source data access, fuzzy state mapping, stage score aggregation and result writeback. The experimental results based on 186 undergraduates, 14 teaching weeks, 12640 interaction records, 2232 test responses, 744 experimental assessment records and 368 discussion texts show that the accuracy of the model reaches 96.8%, and Macro-F1 reaches 95.9%, and it is better than the comparison methods in cross-week stability. The results indicate that when pre-class preparation, classroom interaction, experiment execution, and after-class feedback are included in the unified evaluation chain, the real differences in course implementation can be more accurately identified. There are still two limitations in this paper. On the one hand, the sample source is concentrated on a single course, and the cross-course transfer and cross-semester verification range is still narrow. On the other hand, the deep correlation between text semantics and experimental behavior has not been fully developed, and the utilization of complex expression details by current models is still limited. The follow-up research will expand the coverage of the course, introduce graph structure representation and incremental learning mechanism, and enhance the transfer ability of the model in different chapters, different classes and different teaching cycles. At the same time, the fine-grained experimental process log, semantic coding and online update strategy are combined to further improve the self-adaptive ability, deployment efficiency and continuous analysis performance of the evaluation system. The results can not only be used for the internal evaluation of the course, but also be used as the data basis for the reorganization of teaching tasks, the revision of experimental guidance and the optimization of platform feedback. And it provides a clearer computational support path for subsequent teaching decisions.

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