ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

The Practice of Data-Driven Personalization in Blended Vocabulary Teaching in College English: The Application of an Intelligent Education Platform Integrating Learning and Application

Huangfang Wan[1] *and Peng Wang*[2,*]

[1] Department of English and Law (General Education Department)，College of Technology,
Hubei Engineering University, Xiaogan 432000, Hubei, China
[2] School of Literature, Journalism and Communication, Hubei Engineering University,
Xiaogan 432000, Hubei, China

SUMMARY: *With the transformation of college English teaching to online and offline integration and intelligent support, the problems of individual differences, insufficient memory retention and disconnection of context application in vocabulary learning have become more prominent. Aiming at college English blended vocabulary teaching, this paper constructs an intelligent education platform integrating learning and application, and proposes multi-source behavior event coding, scene-enhanced feature mapping, vocabulary knowledge graph modeling, deep learning mastery state recognition and scene-aware recommendation strategies. The platform converts preview browsing, quiz answering, review interval, reading and writing call and oral task feedback into trainable event sequences, and uses the graph node relationship, contextual attention mechanism and multi-factor scoring model to generate personalized recommendation results. The experiment collects 16 weeks of learning data from 218 students, forms 895205 effective learning events, and completes model training, graph query, cache scheduling and service deployment based on PyTorch, Neo4j, Redis and FastAPI. The results show that the Accuracy, Precision, Recall and F1-score of the proposed model reach 93.8%, 93.2%, 92.7% and 92.9%, respectively. After 8-week intervention, the learning completion rate increased from 78.6% to 93.1%, and the memory retention rate increased from 70.4% to 88.5%. This study provides a verifiable technical path for the data-driven personalized practice of college English vocabulary teaching and the optimization of intelligent education platform.*

KEYWORDS: *Blended vocabulary teaching; Data-driven personalization; Lexical knowledge graph; Intelligent Education Platform*

1 Introduction

College English vocabulary teaching is a basic link in the formation of language ability, and the vocabulary mastery level directly affects students' reading comprehension, listening and speaking expression, writing organization and cross-cultural communication performance [1]. With the wide use of blended teaching platforms, mobile learning tools and intelligent education systems in colleges and universities, students continuously generate behavior logs, answer records, resource access trajectories and application performance data in pre-class preview, classroom interaction, after-class training and language use tasks, which provides

---

*binbinbin88@163.com

https://doi.org/10.65102/is2026967

conditions for vocabulary teaching to shift from experiment-driven to data-driven [2, 3]. Traditional vocabulary teaching mostly relies on a unified vocabulary list, stage tests and teachers' subjective judgment, which makes it difficult to timely identify students' differences in word meaning discrimination, collocation use, context transfer and long-term maintenance, and easily leads to the problems of "learned but not used" and "memorized but not transferred" [4]. For college English learners, vocabulary learning should not stay at the memory level, but also need to be embedded in reading, writing, oral expression and real context tasks, so as to form a stable ability of vocabulary knowledge in continuous application [5-7].

The existing research on intelligent English teaching has focused on learning behavior analysis, online resource recommendation and personalized feedback, but there are still some shortcomings in college English vocabulary teaching scenarios [8]. On the one hand, the data types collected by the platform are scattered, and students 'behaviors such as click, stay, answer, review, writing call and oral use do not form a unified feature expression, which leads to insufficient learning state recognition accuracy. On the other hand, the recommendation of lexical resources is often based on the difficulty, frequency or textbook unit, lacking the modeling of the relationship between word meaning, collocation network, context function and application tasks, and there is a disconnect between the recommendation results and the real language application requirements [9-12]. At the same time, some systems focus on the statistics of learning results and lack a dynamic feedback mechanism for classroom teaching process, which makes it difficult for teachers to timely adjust vocabulary teaching paths according to platform diagnosis results [13].

In order to solve the above problems, this study designs a data-driven application method of personalized intelligent education platform around the requirements of college English blended vocabulary teaching of "learning-application integration". Starting from the collection of multi-source learning data, the study encoded students 'online learning behavior, vocabulary assessment results, review interval, resource access path and application task performance. On this basis, a lexical knowledge graph is constructed, and word form, word meaning, collocation, topic context, difficulty level and application scenario are integrated into the unified semantic network. Further, the deep learning model was used to identify students 'vocabulary mastery status, and the differences in memory retention, semantic understanding and context application were judged. Finally, personalized vocabulary resource recommendation and learning feedback strategies are generated by combining students' learning status and application tasks such as reading, writing, listening and speaking. The study also completed the system deployment and experimental verification through the intelligent education platform, and evaluated the effectiveness of the method from the dimensions of recognition effect, recommendation effect, learning completion rate, vocabulary memory retention rate, application ability improvement and system response efficiency.

The value of this study lies in the integration of individual differences, knowledge structure and language application process in college English vocabulary teaching into the same data modeling framework, which makes vocabulary teaching shift from static content push to dynamic state awareness and precise resource matching. Through the integration of knowledge graph, deep learning and personalized recommendation strategy, the platform can describe students 'vocabulary learning trajectory in more detail, and transform the diagnosis results into executable teaching support plans, which provides technical path and empirical basis for the intelligent upgrading of college English blended vocabulary teaching.

2 The data-driven college English vocabulary learning is designed by using the integrated personalized method

2.1 Hybrid Vocabulary Learning Multi-source data Acquisition and Feature Encoding

The data sources of blended vocabulary teaching have obvious cross-scene characteristics, and the behavioral trajectories formed by students in autonomous learning before class, instant interaction in class, mobile terminal review after class and comprehensive language tasks are not completely consistent. In order to improve the recognition accuracy of vocabulary learning status, this paper integrates the data of learning end, testing end, resource end and application end into the collection scope. It mainly includes word browsing times, audio following time, example sentence clicking behavior, collocation exercise results, spelling error types, target word calls in reading tasks, word repetition frequency in writing texts, and word usage in speaking tasks. All data are anonymized before entering the model and uniformly indexed by student number, timestamp, lexical resource number, and task scenario number, so that discrete learning behaviors can be transformed into continuous computational objects.

For a single word learning behavior, the platform defines it as an event unit, and encodes the event category, resource attribute, dwell time, answer feedback and application scenario into a behavior vector:

$$\mathrm{u_i} = [\mathrm{Emb}(\rho_\mathrm{i})||\mathrm{Enc}(\eta_\mathrm{i})||\log(1+\kappa_\mathrm{i})||\chi_\mathrm{i}||\mathrm{v_i}] \tag{1}$$

where, u_i represents the original encoding vector of the ith vocabulary learning event, ρ_i represents the behavior event category, η_i represents the lexical resource attribute, κ_i represents the stay time, χ_i represents the answer feedback result, and υ_i represents the application scenario to which the behavior belongs. This equation compreszes discrete clicks, continuous time, and task feedback into the same event expression, which provides the basic input for subsequent state recognition.

In the feature mapping stage, we introduce the scene-enhanced coding mechanism to bind the vocabulary learning behavior to the specific language use task, so as to avoid the model only identifying "whether to learn", but not "whether to use in the context". After linear mapping and nonlinear activation, the event vector forms a deep feature representation:

$$\mathrm{v_i} = \mathrm{ReLU}(\mathrm{A_e u_i} + \mathrm{A_s g_i} + \mathrm{c_e}) \tag{2}$$

where, v_i represents the enhanced lexical behavior features, A_e is the event mapping matrix, A_s is the scene mapping matrix, g_i represents the scene embedding for reading, writing, listening or speaking tasks, and c_e is the bias term. Through this processing, the platform can distinguish different learning values of the same word in memory training, semantic discrimination and true expression tasks.

In order to accommodate the batch training of deep learning models, the system builds the input matrix in the order of student learning time. Suppose that a certain student forms h effective behavior events in a continuous window, then its vocabulary learning trajectory matrix is defined as follows:

$$\mathrm{M}_{\mathrm{r}}^{(\mathrm{h})} = \begin{bmatrix} \mathrm{v}_{\mathrm{r},1} \\ \mathrm{v}_{\mathrm{r},2} \\ \cdots \\ \mathrm{v}_{\mathrm{r},\mathrm{h}} \end{bmatrix}, \mathrm{m}_{\mathrm{r}}^{(\mathrm{h})} = \mathrm{MaskAvg}(\mathrm{M}_{\mathrm{r}}^{(\mathrm{h})}, \mathrm{o}_{\mathrm{r}}^{(\mathrm{h})}) \quad (3)$$

where, $\mathrm{M}_{\mathrm{r}}^{(\mathrm{h})}$ represents the behavior input matrix formed by student r in a time window of length h, $\mathrm{v}_{\mathrm{r,j}}$ represents the JTH lexical behavior feature in the window, $\mathrm{o}_{\mathrm{r}}^{(\mathrm{h})}$ represents the effective behavior mask, and $\mathrm{M}_{\mathrm{r}}^{(\mathrm{h})}$ represents the learning trajectory representation after mask average pooling. The matrix not only retains the order of behavior occurrence, but also reduces the interference of missing records and invalid clicks on model training, so that the platform can more stably depict students 'vocabulary learning process. The vocabulary learning behavior event encoding and the model input matrix design are shown in Table 1.

Table 1: Vocabulary learning behavior event encoding and model input matrix design table

Behavior Event Type	Original Behavior Meaning	Encoding Method	Input Dimension or Value Range	Model Function
Vocabulary Preview Browsing Event	Students view target words, definitions, phonetic symbols, and example sentences before class	Event category embedding combined with resource attribute encoding	32-dimensional event embedding; resource difficulty level 1–5	Identifies students’ initial exposure to new words
Audio Shadowing Training Event	Students play vocabulary audio and complete shadowing practice	Duration normalization combined with speech completion marker encoding	Shadowing duration 0–180 s; completion marker 0 or 1	Identifies students’ participation in spoken input practice
Word Meaning Discrimination Event	Students complete synonym, word meaning selection, and contextual judgment tasks	Joint encoding of answer result, response time, and error type	Correctness marker 0 or 1; response time 0–120 s	Evaluates word meaning understanding and discrimination ability
Collocation Application Practice Event	Students complete phrase collocation, sentence completion, and translation tasks	Collocation type encoding combined with score interval encoding	8 collocation types; task score 0–100	Identifies the transfer degree from vocabulary memory to application
Reading and Writing Usage Event	Students actively use target words in reading annotation or writing tasks	Encoding of word usage frequency and contextual matching degree	Usage frequency 0–20 times; matching degree 0–1	Measures vocabulary application effectiveness in authentic language tasks
Review Revisit Event	Students revisit learned vocabulary during spaced review	Time interval encoding combined with forgetting risk marker	Review interval 1–30 days; risk level low, medium, or high	Supports subsequent personalized review resource recommendation

Table 1 shows that the platform does not input a single performance data into the model, but a multi-dimensional event matrix composed of learning behaviors, language tasks, resource attributes and feedback results. Through this encoding method, students 'vocabulary learning process is transformed into trainable, traceable and updatable feature sequences, which lays a data foundation for the subsequent construction of vocabulary knowledge graph and vocabulary mastery state recognition.

2.2 Construction of lexical knowledge graph for integration of learning and application

In college English vocabulary teaching, vocabulary knowledge is not only represented by word interpretation and spelling, but also includes word meaning extension, grammatical function, collocation, thematic context, discourse position and task usage. In order to enable the intelligent education platform to support "learning vocabulary" and "using vocabulary" at the same time, this paper constructs a vocabulary knowledge graph for the integration of learning and application, which organizes the textbook vocabulary, CET-4 and CET-6 high-frequency words, classroom expansion words, example sentence corpus, reading text, writing task and oral expression scene into a computable semantic network. Graph nodes include word form nodes, word sense nodes, collocation nodes, example sentence nodes, topic nodes, application task nodes and error type nodes, and edge relations include synonymous association, antisense association, derivation association, collocation association, context association, task association and error transfer association. Through graph structure modeling, the platform is able to extend from single word training to overall recommendation of word groups, semantic chains, and application task paths. The framework of data-driven vocabulary learning using the all-in-one personalization approach is shown in Figure 1.

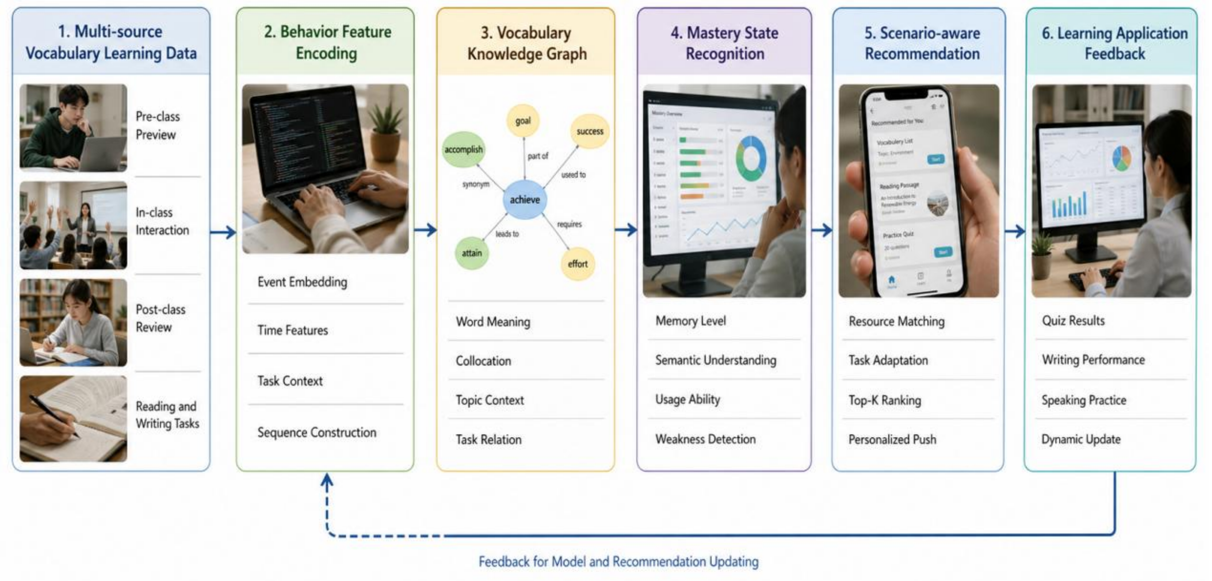

Figure 1: Framework diagram of data-driven vocabulary learning using integrated personalization method

In the formal construction of graph, lexical knowledge graph is defined as a heterogeneous semantic network composed of node set, relation set and triple set:

$$\mathcal{K}_{\mathrm{vocab}} = (\mathcal{P}_{\mathrm{node}}, \mathcal{L}_{\mathrm{rel}}, \mathcal{T}_{\mathrm{tri}}), \quad \mathcal{T}_{\mathrm{tri}} = \{(\mathrm{p_a}, \mathrm{l_{ab}}, \mathrm{p_b}) \mid \mathrm{p_a}, \mathrm{p_b} \in \mathcal{P}_{\mathrm{node}}, \mathrm{l_{ab}} \in \mathcal{L}_{\mathrm{rel}}\} \tag{4}$$

where, K_{vocab} represents the lexical knowledge graph, P_{node} represents the set of graph nodes, L_{rel} represents the set of semantic relations, T_{tri} represents the set of triples, p_a and p_b represent two different lexical knowledge nodes, and l_{ab} represents the type of relationship between them. Through the triple organization method, the platform can connect "word - word meaning - collocation - context - task" into a continuous knowledge path, which provides a structured semantic basis for subsequent recommendation algorithms.

In the node representation stage, the text semantics, course attributes and task functions of vocabulary nodes are fused and encoded, so that the graph nodes not only contain linguistic meanings, but also reflect teaching use scenarios. The initial node representation is defined as follows:

$$q_a = \Phi_{txt}(d_a) \oplus \Phi_{course}(b_a) \oplus \Phi_{task}(y_a) \tag{5}$$

where, q_a represents the initial embedding representation of node pa, d_a represents the interpretation, example sentence or text description corresponding to the node, b_a represents the attribute information of the word in the course unit, difficulty level and teaching goal, ya represents the reading, writing, listening or speaking task type associated with the node, and $\oplus$ represents the vector splicing operation. This encoding method can avoid vocabulary nodes only retaining dictionary definitions, and make them have both course orientation and application task orientation.

In the edge weight calculation stage, the graph needs to judge the semantic connection strength between different lexical knowledge nodes. In this paper, semantic similarity, co-occurrence frequency and task transfer correlation are jointly incorporated into edge weight estimation, and the relationship weight is calculated as follows:

$$\theta_{ab}^{rel} = \mu_1 \cdot \mathrm{Cos}(q_a, q_b) + \mu_2 \cdot \frac{\mathrm{Freq}(p_a, p_b)}{\mathrm{Freq}(p_a) + \mathrm{Freq}(p_b)} + \mu_3 \cdot \mathrm{TaskSim}(y_a, y_b) \tag{6}$$

where, θ_{ab}^{rel} represents the relationship weight between node p_a and node p_b, μ_1, μ_2, μ_3 are the three types of relationship contribution coefficients, Cos(·) represents the cosine similarity of semantic vectors, $\mathrm{Freq}(p_a,p_b)$ represents the co-occurrence number of two nodes in the learning corpus or task corpus. $\mathrm{TaskSim}(y_a,y_b)$ represents the functional similarity between two task scenarios. Through the edge weight design, the graph can identify high-frequency collocation relationships, and can also find low-frequency application transfer relationships with high teaching value.

In the graph inference phase, the platform updates node representations through neighborhood aggregation, which enables lexical nodes to absorb information from neighboring word senses, collocations, and application tasks. The node update process is defined as follows:

$$z_a = \mathrm{GELU}\left(H_0 q_a + \sum\nolimits_{p_b \in \mathcal{N}_a^{kg}} \theta_{ab}^{rel} H_l q_b\right) \tag{7}$$

where, z_a represents the node representation after graph propagation, H0 represents the self-node mapping matrix, H_l represents the neighborhood mapping matrix corresponding to the relation type, $\mathcal{N}_a^{kg}$ represents the knowledge neighborhood set of node pa, and GELU(·) represents the nonlinear activation function. Through this process, a target word is no longer an isolated recommendation object, but can participate in the personalized decision together with its synonyms, fixed collocations, discourse topics and task requirements.

After the construction of lexical knowledge graph, the platform can locate the weak nodes of students according to their current learning state, and generate a progressive resource combination along the path of the graph. For example, when students are weak in the "word sense discrimination" node, the system can extend the recommendation along the edges of synonyms, antonyms and contextual example sentences. When students perform insufficiently at the "writing call" node, the system can preferentially push collocation templates, discourse sentence patterns, and thematic writing tasks. Therefore, the graph becomes the middle layer connecting vocabulary memory, semantic understanding and language use, which makes the subsequent deep learning state recognition and personalized recommendation have stronger semantic interpretation ability and teaching adaptability.

2.3 The Recognition model of Students 'Vocabulary mastery state Based on deep learning

The state of students' vocabulary mastery is obviously dynamic, and the same student may show different changes in the three levels of vocabulary memory, semantic understanding and application output. It is easy to ignore implicit information such as review interval, task scene, error type and context call only by relying on stage test scores. Therefore, this paper constructs a student's vocabulary mastery state recognition model based on deep learning, and the behavior sequence coding, the semantic representation of vocabulary knowledge graph and learning feedback records are jointly input into the model. The model adopts the structure of "temporal encoding-semantic graph encoding-feature fusion-state decoding", which not only captures the law of forgetting and strengthening in the continuous learning process of students, but also introduces the semantic association between vocabulary nodes, so that the platform can identify the differences in students 'memory retention, semantic discrimination and real application. Figure 2 shows the overall structure of the student vocabulary mastery state recognition model.

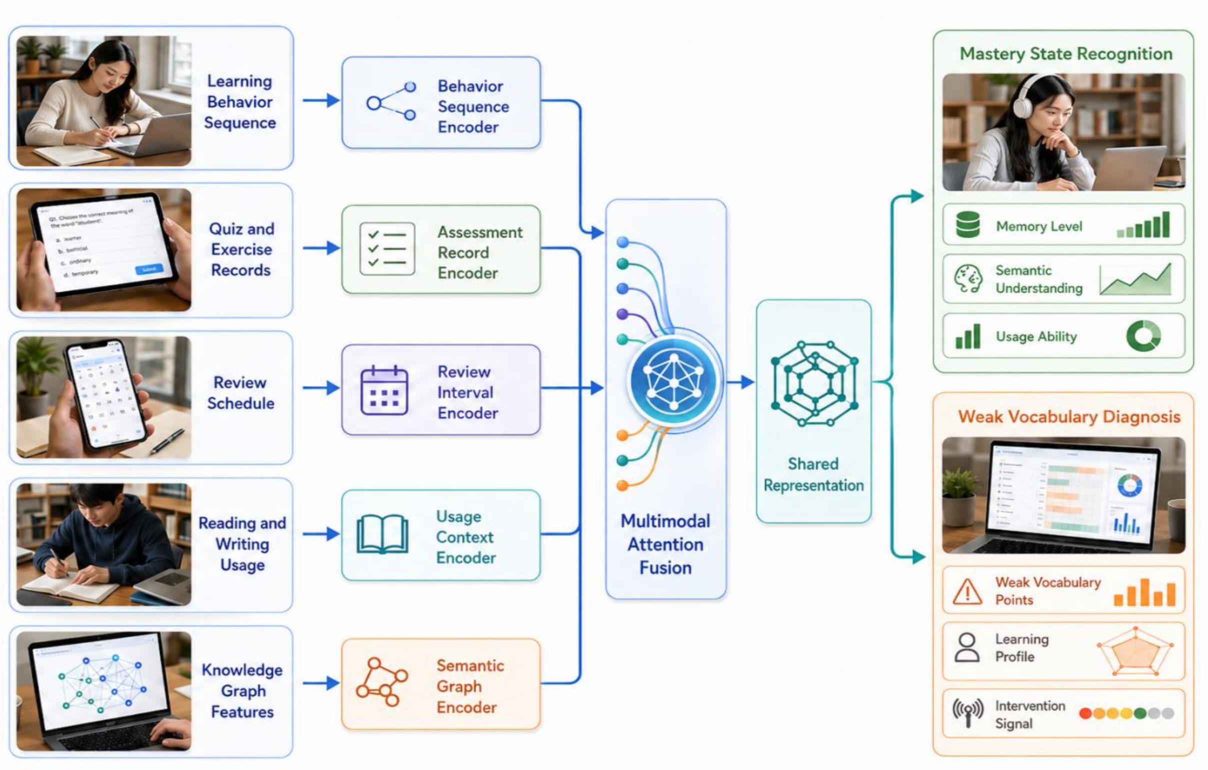

Figure 2: Architecture diagram of student vocabulary mastery state recognition model based on deep learning

For the t-th lexical behavior feature of student n in a successive learning window, let its input be represented as $\xi_{n,t}$. In this paper, bi-directional gated temporal coding structure is used to extract pre-and post-behavior dependencies:

$$\vec{\alpha}_{n,t} = \mathrm{GRU}_f(\xi_{n,t}, \vec{\alpha}_{n,t-1}), \overleftarrow{\alpha}_{n,t} = \mathrm{GRU}_b(\xi_{n,t}, \overleftarrow{\alpha}_{n,t+1}) \tag{8}$$

where, $\vec{\alpha}_{n,t}$ represents the forward learning trajectory implicit representation and $\overleftarrow{\alpha}_{n,t}$ represents the reverse learning trajectory implicit representation. This structure can simultaneously capture the influence of recent review behavior on the current mastery state, and the reverse check of subsequent application performance on the previous learning quality.

In order to avoid the model processing all behavior events on average, we introduce a contextual attention mechanism to highlight high-value behavior segments, such as word sense discrimination questions that occur repeatedly incorrectly, target words that are not correctly invoked in writing, and words that are still forgotten after review interval. The attention weights are calculated as follows:

$$\omega_{n,t} = \frac{\exp\left(\lambda_c^{T} \tanh(B_c[\vec{\alpha}_{n,t}||\overleftarrow{\alpha}_{n,t}] + \delta_c)\right)}{\sum_{\tau=1}^{T_n} \exp\left(\lambda_c^{T} \tanh(B_c[\vec{\alpha}_{n,\tau}||\overleftarrow{\alpha}_{n,\tau}] + \delta_c)\right)} \tag{9}$$

where $\omega_{n,t}$ represents the importance weight of the TTH behavior event, λ_c represents the context attention parameter, B_c represents the attention mapping matrix, δ_c represents the bias vector, and Tn represents the effective number of behaviors of student n in the current window. Through this mechanism, the model can filter the key behaviors that really affect the mastery state from a large number of clicks and practice records.

In the semantic graph channel, the platform extracts the student-related weak word nodes, associated collocation nodes and application task nodes from the lexical knowledge graph, and generates the graph semantic vector κn. Further fusion of temporal attention output and graph semantic vector:

$$\varphi_n = \mathrm{LayerNorm}\left(R_s \sum_{t=1}^{T_n} \omega_{n,t} [\vec{\alpha}_{n,t}]||\overleftarrow{\alpha}_{n,t}] + R_g \kappa_n + R_p \psi_n\right) \tag{10}$$

where, φ_n represents the fusion representation of students 'vocabulary mastery state, R_s represents the temporal feature mapping matrix, R_g represents the semantic mapping matrix of the graph, R_p represents the mapping matrix of the learning portrait, and ψ_n represents the features of students 'historical learning portrait. The fusion method made the model not only focus on students' current learning trajectory, but also combine long-term learning tendency and word semantic structure.

Finally, the state decoder adopts a multi-task output mode to simultaneously identify the memory level, semantic understanding level and application ability. The output result is defined as follows:

$$\widehat{\Omega}_n = [\mathrm{Softmax}(D_m \varphi_n + \varepsilon_m), \mathrm{Softmax}(D_u \varphi_n + \varepsilon_u), \mathrm{Sigmoid}(D_a \varphi_n + \varepsilon_a)] \tag{11}$$

where, $\widehat{\Omega}_n$ represents the vocabulary mastery state output set of student n; D_m, D_u and D_a represent the decoding matrices corresponding to memory level, semantic understanding and application ability respectively; ε_m, ε_u and ε_a are the corresponding bias terms. The output is not only used to judge whether the student has mastered the target word, but also to locate weak vocabulary points, generate learning portraits and trigger subsequent intervention signals.

The innovation of the model is that the vocabulary learning process is extended from a single test decision to a state recognition process driven by multi-source behavior sequences and knowledge graph semantics. The temporal channel depicts the change of learning trajectory, the graph channel supplements the semantic relationship of words, and the fusion decoding layer converts the recognition results into interpretable learning state labels. Therefore, the platform can provide more stable status input for subsequent personalized recommendation strategies, and make the word resource push change from "recommended by unit" to "recommended by mastered status and application requirements".

2.4 Personalized recommendation strategy integrating learning state and application scenario

After completing the recognition of students' vocabulary mastery status, the intelligent education platform needs to transform the recognition results into an executable vocabulary learning support scheme. Personalized recommendation for college English vocabulary learning should not only push resources based on students' current scores, but also consider their memory stability, semantic understanding depth, context application ability, current classroom task types and semantic attributes of resources themselves. Based on the results of vocabulary knowledge graph and mastery state recognition, this paper constructs a personalized recommendation strategy that integrates learning states and application scenarios, so that the platform can generate differentiated vocabulary resources and application tasks for students in different scenarios such as pre-class preview, classroom interaction, after-class review, reading input, writing output and oral expression.

The recommendation module first jointly represents the students' vocabulary mastery status and the current application scenario. Let the mastery state vector of student e be Γ_e, the current learning scenario vector be Σo, and the scenario task constraint feature be $\Delta_{e,o}$, then the recommendation intention generated by the platform is expressed as follows:

$$\Pi_{e,o} = \mathrm{LayerNorm}\left(P_1\Gamma_e + P_2\Sigma_o + P_3\Delta_{e,o} + \varpi_0\right) \tag{12}$$

where, $\Pi_{e,o}$ represents the recommended intention vector of student e under scenario o, P_1, P_2, and P_3 are the mapping matrices of different feature channels, and ϖ_0 is the bias vector. This representation can integrate "how well" and "what task is currently used to complete" into the recommendation calculation process.

In the candidate resource recall stage, the platform selects candidate resources related to students' weak vocabulary, target topics and application tasks from the vocabulary knowledge graph and resource library. The semantic representation of a candidate resource j is denoted as Λj, and the initial matching degree between it and the recommendation intention is defined as follows:

$$\zeta_{e,j} = \mathrm{Sigmoid}\left(U_1^{\top}\Pi_{e,o} + U_2^{\top}\Lambda_j + U_3^{\top}\left(\Pi_{e,o} \odot \Lambda_j\right)\right) \tag{13}$$

where $\zeta_{e,j}$ represents the initial matching score of candidate resource j to student e, U_1, U_2, U_3 are the matching parameter vectors, and $\odot$ represents the element-by-element interaction operation. In this way, the system can identify the matching relationship between resource content and student status, such as matching students with weak semantic discrimination to synonyms comparison resources, and matching students with insufficient writing call to collocation templates and theme expression tasks.

In order to avoid the recommendation results only pursuing content similarity and ignoring teaching adaptability, this paper computes state matching, graph association, scene transfer and novelty gain into unified scoring features, and takes resource difficulty and learning burden as risk penalty terms. The comprehensive recommendation score of a candidate resource is defined as follows:

$$\mathfrak{S}_{\mathrm{e,j}} = \beta^{\mathrm{T}} \mathrm{F}_{\mathrm{e,j}} - \mathrm{Risk}_{\mathrm{e,j}} \tag{14}$$

where, $\mathfrak{S}_{\mathrm{e,j}}$ represents the comprehensive recommendation score of student e to candidate resource j; $\mathrm{F}_{\mathrm{e,j}}$ represents the normalized scoring feature vector composed of state matching, graph association, scene adaptation and novelty gain; β represents the weight vector of each scoring feature; $\mathrm{Risk}_{\mathrm{e,j}}$ represents the cognitive load penalty term formed by resource difficulty, task length and historical error rate. The design not only retains the multi-factor scoring logic, but also avoids the long formula, which makes the subsequent dynamic weight update more concise.

After the comprehensive scoring is completed, the platform generates a personalized recommendation set according to the ranking results:

$$\mathcal{O}_{\mathrm{e}}^{\mathrm{K}} = \mathrm{TopK}\left(\left\{\mathfrak{S}_{\mathrm{e,j}} \mid \mathrm{j} \in \mathcal{C}_{\mathrm{e,o}}\right\}\right) \tag{15}$$

where, $\mathcal{O}_{\mathrm{e}}^{\mathrm{K}}$ represents the set of top K recommended resources for student e, and $\mathcal{C}_{\mathrm{e,o}}$ represents the pool of candidate resources recalled in the current scenario. The recommended collection not only includes vocabulary definitions, example sentences and exercises, but also includes reading paragraphs, writing sentence patterns, oral expression tasks and interval review reminders, so as to form a resource combination for learning and application cohesion. Figure 3 shows the closed loop of personalized lexical resource recommendation and dynamic feedback.

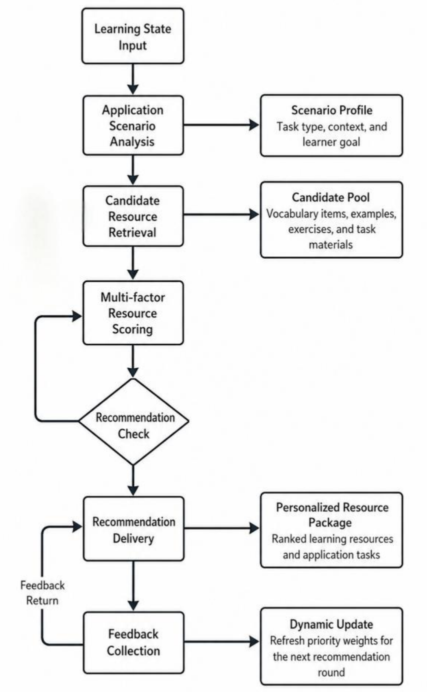

Figure 3: Closed-loop diagram of personalized vocabulary resource recommendation and dynamic feedback

The feedback error driven method is used to adjust the weight of the scoring factor in the dynamic update step. Let the true feedback revenue $\mathcal{G}_{e,j}^{(t)}$ after the t-th recommendation round, the platform predicted revenue $\hat{\mathcal{G}}_{e,j}^{(t)}$, and the rating weight vector $\beta^{(t)}$, then the update rule is as follows:

$$\beta^{(t+1)} = \beta^{(t)} + \iota\left(\mathcal{G}_{e,j}^{(t)} - \hat{\mathcal{G}}_{e,j}^{(t)}\right)\nabla_{\beta}\mathfrak{S}_{e,j}^{(t)} - \iota\varrho\beta^{(t)} \tag{16}$$

where, ι denotes the update step and ϱ denotes the coefficient of the regularization constraint. If a certain type of recommended resources can significantly improve students' memory retention rate or context calling ability, the weight of its related scoring factors will be enhanced. If the resource causes the completion rate to decrease or the load to be too high, the platform will reduce the priority of its subsequent recommendation. This mechanism enables the recommendation strategy to adjust continuously with the change of students 'learning trajectory. Table 2 shows the scoring factors and dynamic update rules of candidate resources for personalized recommendation.

Table 2: Personalized recommendation candidate resource scoring factors and dynamic update rule table

Scoring Factor	Calculation Basis	Initial Weight	Dynamic Update Method	Recommendation Function
State Matching Factor	Recognition results of students’ memory level, semantic understanding, and usage ability	0.30	Adjusted according to task completion rate and mastery improvement	Improves the match between resources and students’ current weak states
Graph Association Factor	Association strength between target words and synonym, collocation, topic context, and application task nodes	0.22	Adjusted according to subsequent error transfer and vocabulary recurrence	Ensures semantic extensibility of recommended resources
Scenario Transfer Factor	Adaptability between reading, writing, listening, speaking tasks and candidate resources	0.20	Adjusted according to application task scores and contextual usage frequency	Promotes the transfer from vocabulary memory training to authentic use
Cognitive Load Factor	Comprehensive estimation of resource difficulty, task length, historical error rate, and learning duration	0.16	Reversely adjusted according to abandonment rate, timeout rate, and repeated error rate	Prevents learning interruption caused by excessive resource difficulty
Novelty Gain Factor	Difference and supplementary value between candidate resources and students’ learned resources	0.12	Adjusted according to new-word retention rate and extension task performance	Prevents repetitive resource pushing and expands the vocabulary network

Table 2 shows that personalized recommendation is not simply ranked by similarity, but is jointly determined by state matching, graph association, scene transfer, load control and novelty gain. By dynamically updating the rules, the platform could continuously revise the recommendation weights according to students 'real feedback, making the vocabulary learning resources push closer to individual differences and language application requirements. This strategy provides a core decision-making mechanism for the subsequent system deployment and experimental verification of intelligent education platform.

3 Experimental design and system deployment of intelligent education platform

3.1 College English Vocabulary Learning Dataset construction and preprocessing process

Based on the actual operation data of the intelligent education platform in the blended vocabulary teaching of college English, this study constructs an experimental data set. The data collection period is 16 weeks. The research objects are 218 first-year non-English majors in a university, covering 6 teaching classes. A total of 936,480 vocabulary learning behavior data were recorded on the platform, including 185,620 vocabulary preview records before class, 214,360 records of classroom interaction and test, 267,940 records of after-class review and error visit, 168,750 records of reading and writing task call, and 99,810 records of oral and comprehensive application task. The vocabulary resource library contains 3,200 college English core vocabulary, 1,150 expanded vocabulary, 12,600 example sentence resources, 8,430 vocabulary collocation resources, 6,800 test questions, 420 reading passages, 180 writing tasks, and 96 oral expression tasks. The above data can completely cover the learning process of students from vocabulary exposure, understanding, memory to application output.

Raw data needs to be cleaned, encoded, aligned, and sample partitioned before entering the model. For repeated clicks, abnormal stays, invalid resource access, missing timestamps and non-learning behavior records, the platform used rule filtering and threshold judgment to eliminate, deleted a total of 41,275 invalid records, and finally retained 895,205 valid learning events. For similar behaviors that are triggered continuously in a short time, the system merges them according to the 30-second event window to avoid the deviation of behavior frequency caused by mechanical clicks. The lexical resource information is labeled according to word meaning category, difficulty level, collocation type, topic context and task attribute. Student behavior data are transformed into features such as event category, reaction time, accuracy rate, review interval, resource stay time and application performance. The use of target words in reading and writing tasks is obtained by text matching and semantic similarity calculation, which is used to judge whether students can use the target words in the real context.

After preprocessing, the system constructs a sequence of vocabulary learning events using student number, vocabulary number, task number and timestamp as the joint index. The dataset was non-overlapping divided according to the individual students, and the ratio of training set, validation set and test set was set to 7：1：2, corresponding to 152, 22 and 44 students, to avoid the high evaluation caused by the same student behavior appearing in the training and testing phase at the same time. All continuous variables are normalized, discrete variables are input into the model by embedding coding, low-frequency words and very short behavior sequences are retained by masking mechanism but not directly involved in the determination of core states. After the above processing, the experimental data can support the vocabulary mastery status recognition, personalized recommendation ranking and platform feedback update experiments at the same time, and provide a stable data basis for subsequent model training and result analysis.

3.2 Model training parameter configuration and platform deployment scheme

The model training phase focuses on two tasks: vocabulary mastery status recognition and personalized recommendation. The experimental environment uses Windows Server 2019 operating system, the core algorithm is implemented under the framework of Python 3.10 and PyTorch 2.1, the GPU is used to accelerate the training of deep learning models, and the CPU is responsible for platform service scheduling and data preprocessing. The training data are generated from the sequence of effective learning events constructed in Section 3.1, and the input features include learning behavior encoding, quiz feedback, review interval, reading and writing call features, and lexical knowledge graph embedding. AdamW optimizer was used for model training, the learning rate was set to 0.0005, the batch size was set to 128, the maximum training round was 100, and an early stopping mechanism was introduced to prevent overfitting. The loss function is composed of state recognition classification loss, recommendation ranking loss and regular constraint term, which ensures that the model can not only accurately judge students 'vocabulary mastery status, but also provide stable features for subsequent resource recommendation. To ensure the reproducibility of the experiment, the model training parameters and platform deployment configuration are shown in Table 3.

Table 3: Model training parameters and platform deployment configuration table

Configuration Category	Specific Content	Parameter Setting	Technical Function
Operating System	Server runtime environment	Windows Server 2019	Supports platform deployment and model training
Programming Environment	Deep learning development framework	Python 3.10, PyTorch 2.1	Implements the mastery state recognition model and recommendation algorithm
Hardware Configuration	Computing and inference devices	Intel Xeon Silver 4214R, NVIDIA RTX 3090, 64 GB RAM	Provides computing power for model training and online inference
Optimizer	Model parameter update method	AdamW	Improves gradient update stability and reduces overfitting risk
Learning Rate	Model training step size	0.0005	Controls model convergence speed and training stability
Batch Size	Number of samples per training batch	128	Balances memory usage and gradient estimation stability
Training Epochs	Maximum number of iterations	100 epochs, early stopping threshold of 10 epochs	Prevents continued training after validation performance declines
Embedding Dimension	Representation dimension of behavior and vocabulary features	128 dimensions	Unifies behavior, resource, and graph feature representations
Sequence Length	Behavior window length	40 events	Preserves students’ continuous vocabulary learning trajectories
Platform Backend	Service interface deployment mode	FastAPI, Docker, Nginx	Supports model service encapsulation and multi-terminal access
Data Storage	Platform database configuration	MySQL, Redis, Neo4j	Stores resource data, cached data, and vocabulary graph relations respectively

Students and teachers access the back-end service through the Web interface. The back-end writes the learning behavior into the database, and calls the model service to complete the state recognition and recommendation calculation. Neo4j is used to store the vocabulary knowledge graph, Redis is used to cache high-frequency recommendation results, and MySQL is used to save user behavior, task records and evaluation results. The deployment scheme can ensure the stable operation of model training, online inference, resource scheduling and feedback update in the same experimental environment, and provide unified technical conditions for the result analysis in Chapter IV.

4 Results and analysis

4.1 Comparative analysis of vocabulary mastery status recognition effects under different models

In order to verify the effectiveness of the proposed model in the recognition of students 'vocabulary mastery state, SVM, Random Forest, BiLSTM and Transformer are selected to compare with the model in this paper, and the evaluation indicators include Accuracy, Precision, Recall and F1-score. Figure 4 shows the comparison of the recognition performance of each model.

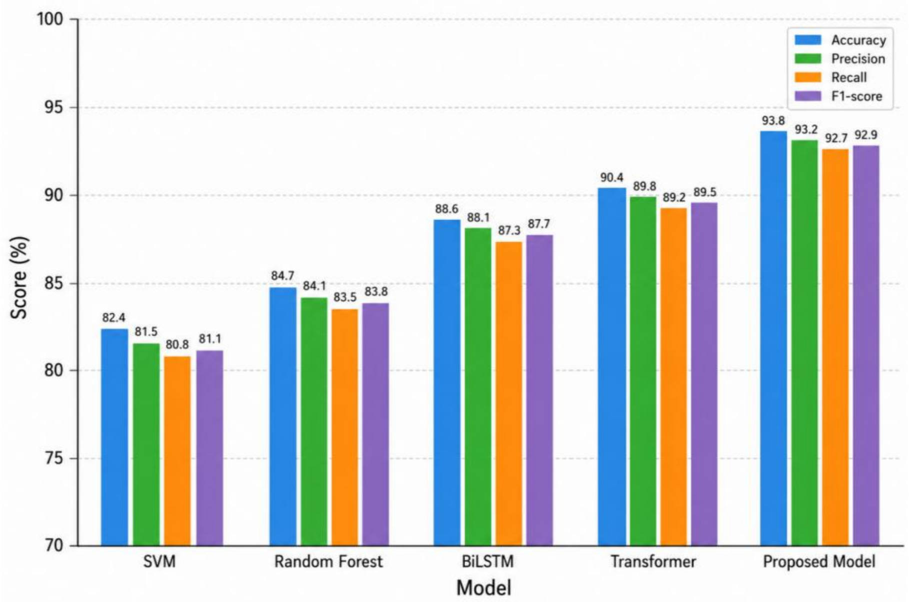

Figure 4: Bar chart of vocabulary mastery state recognition performance comparison of different models

Figure 4 shows that the performance of traditional machine learning models in multi-source vocabulary learning behavior modeling is relatively limited, the Accuracy of SVM is 82.4%, and the F1-score is 81.1%. Random Forest has a slight improvement, with an Accuracy of 84.7%, but the description of the temporal relationship and semantic association of learning behaviors is still not sufficient. After introducing sequence modeling into BiLSTM, the Accuracy is improved to 88.6%, which indicates that the vocabulary learning trajectory plays an important role in the judgment of mastery state. Transformer is further improved to 90.4%, reflecting the advantages of attention mechanism in the capture of key learning behaviors. The proposed model achieves the highest results on the four indicators, with

Accuracy, Precision, Recall and F1-score reaching 93.8%, 93.2%, 92.7% and 92.9%, respectively. This shows that after fusing the behavior sequence, lexical knowledge graph and application scene features, the model can more accurately distinguish the differences in students 'state in memory retention, semantic understanding and vocabulary use.

4.2 Influence of personalized vocabulary recommendation on learning completion rate and memory retention rate

In order to further verify the influence of personalized vocabulary recommendation strategy on students 'continuous learning effect, this paper took the 8-week teaching intervention cycle as the observation object, and calculated the changes of students 'vocabulary task completion rate and memory retention rate in the intelligent education platform. The learning completion rate mainly reflected the students' implementation of the platform recommended resources, practice tasks and application tasks, and the memory retention rate was comprehensively calculated according to the interval review test, the wrong question return visit results and the target word recognition accuracy. The personalized recommendation strategy dynamically adjusts the resource push order according to students 'mastery status, application scenarios and knowledge graph association results, so that students can obtain more matching vocabulary practice and application tasks at different stages. The change trend of the two indicators under the personalized recommendation intervention is shown in Figure 5.

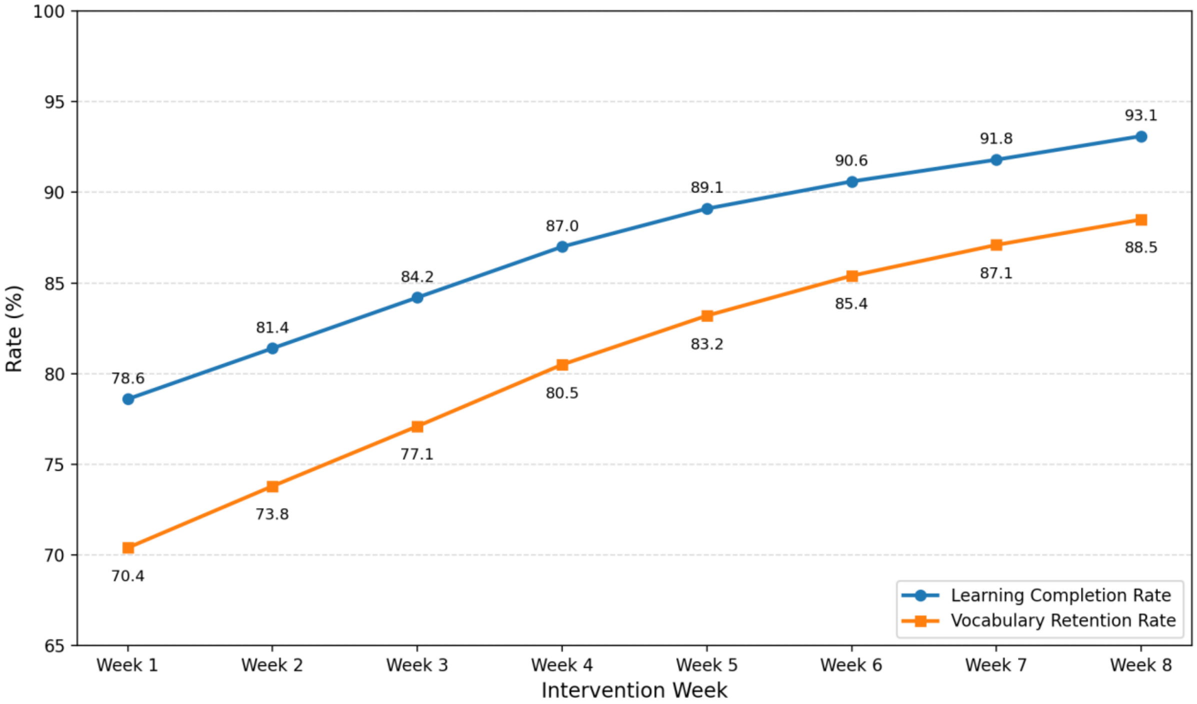

Figure 5: Change curve of learning completion rate and memory retention rate under personalized recommendation intervention

As can be seen from Figure 5, with the continuous intervention of personalized recommendation, the vocabulary learning completion rate and memory retention rate of students show a steady upward trend. The learning completion rate increased from 78.6% in the first week to 93.1% in the eighth week, an increase of 14.5 percentage points, indicating that students 'acceptance and execution of vocabulary resources were significantly enhanced after the platform pushed tasks according to their learning status. The retention rate increased from 70.4% to 88.5%, an increase of 18.1 percentage points, which was higher than the completion rate, indicating that the recommendation strategy not only improved the task participation, but also promoted the long-term retention of vocabulary knowledge. After the fifth week, the growth of the two curves tended to be stable, indicating that students gradually formed a stable review rhythm and application habits. On the whole, the recommendation mechanism combining mastery state recognition, scene adaptation and feedback update can effectively alleviate the problems of task duplication, resource mismatch and high forgetting rate in traditional vocabulary learning.

4.3 Analysis of the relationship between learning behavior characteristics and the improvement of vocabulary application ability

In order to analyze the influence of students 'learning behavior characteristics on the improvement of vocabulary application ability, this paper selected three dimensions of review frequency, context call frequency and vocabulary application score for correlation modeling. Among them, the frequency of review reflects students' continuous contact with the target word, the frequency of context call reflects students' active use of words in reading, writing and speaking tasks, and the vocabulary application score is calculated by combining writing accuracy, collocation use quality and context matching degree. Figure 6 shows the 3D distribution relationship between learning behavior characteristics and vocabulary utilization ability.

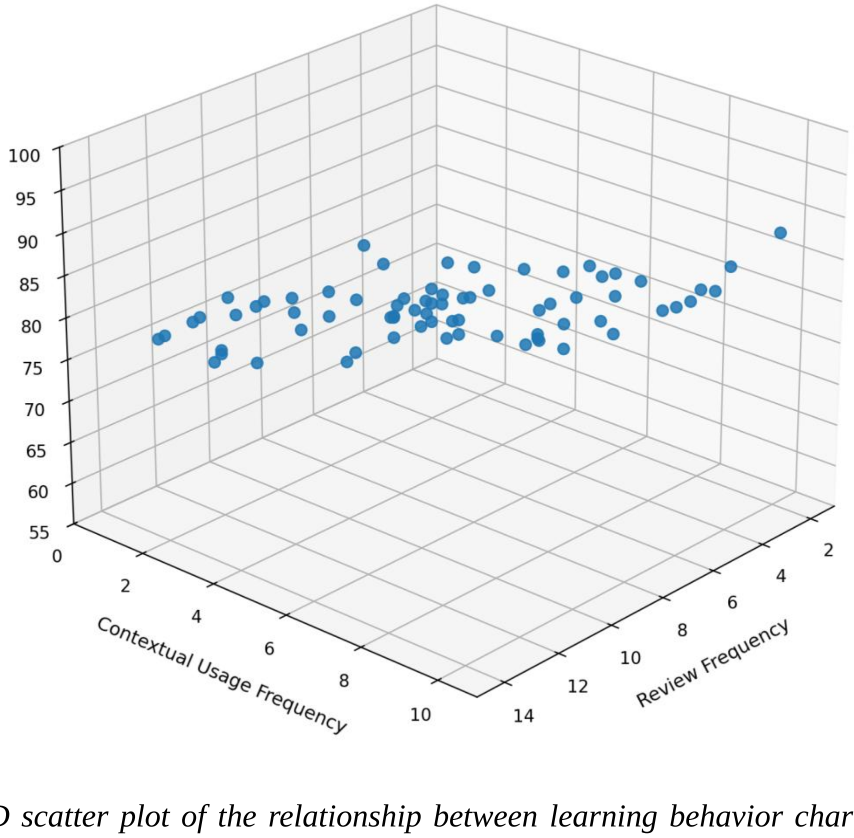

Figure 6: 3D scatter plot of the relationship between learning behavior characteristics and vocabulary utilization ability

As can be seen from Figure 6, students' vocabulary application scores show an obvious upward trend with the increase of review frequency and context call frequency. When the frequency of review is less than 5 times and the frequency of context invocation is less than 3 times, the vocabulary application scores of most samples are concentrated below 70 points, indicating that a single memory or shallow practice is difficult to support stable application. As the frequency of review increased to 8-12 times and the frequency of context call increased to more than 6 times, the sample points gradually clustered to the high region, and the vocabulary application score generally reached more than 82 points. In particular, students with higher frequency of context calls can obtain better application performance even if the frequency of review is at a moderate level, indicating that "using vocabulary in the task" can promote vocabulary transfer more than simple repetition memorization. On the whole, continuous review and contextualized use work together to improve vocabulary ability, which also verifies the necessity of learning and using integrated recommendation strategies.

4.4 Learn to verify the feedback effect of the platform under the integrated task

In order to verify the support effect of the platform feedback mechanism in the integrated task of learning and application, this paper sets up two comparison conditions of "no intelligent feedback" and "with intelligent feedback", and evaluates the feedback effect of the platform from six dimensions: task completion, vocabulary transfer, feedback timeliness, learning participation, error correction and teaching support. Figure 7 shows the effect of platform teaching support under different feedback mechanisms.

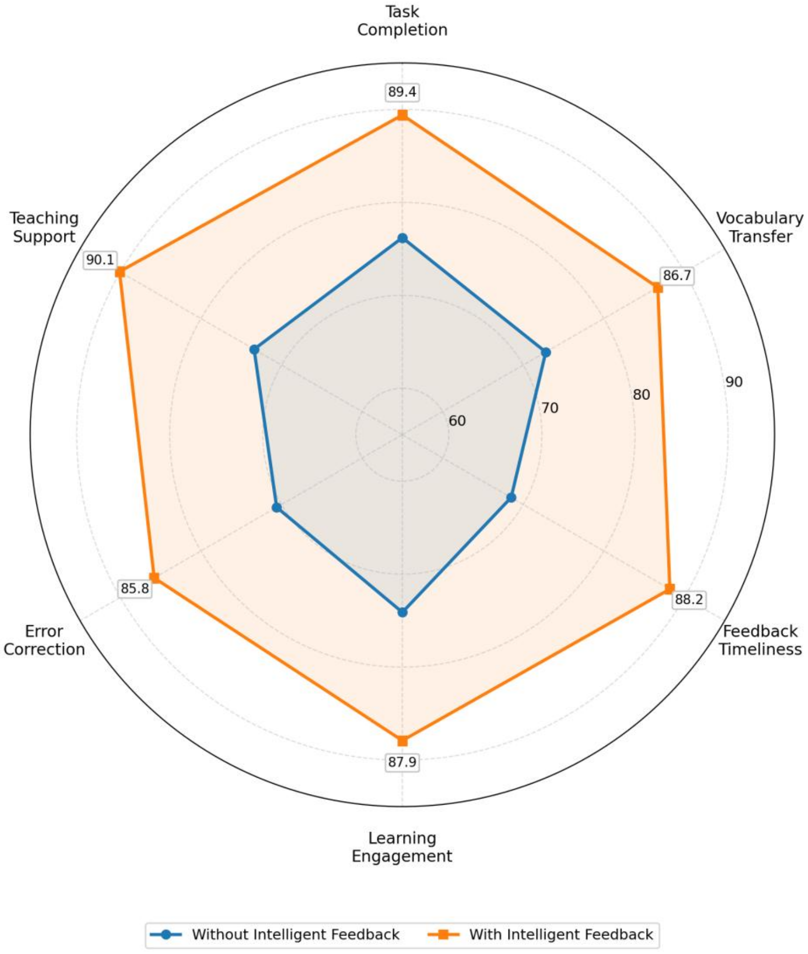

Figure 7: Radar chart of platform teaching support effect under different feedback mechanisms

Figure 7 shows that after the introduction of intelligent feedback, all evaluation dimensions appear to be significantly improved. Among them, the score of teaching support increased from 73.4 to 90.1, indicating that the diagnosis results of the teacher side and the recommendation feedback of the platform could provide a clearer basis for classroom intervention. The feedback timeliness was improved from 68.5 to 88.2, indicating that the platform can quickly generate prompts according to students' answers, review and application performance. The vocabulary transfer score increased from 72.8 to 86.7, indicating that the context example sentences, collocation correction and application task guidance helped students to transfer vocabulary from memory training to reading and writing use. The error correction score is improved from 70.6 to 85.8, and the task completion score is improved from 76.2 to 89.4, which further proves that platform feedback can reduce repetitive errors and improve the quality of task execution. On the whole, the intelligent feedback mechanism enhances the closed-loop adjustment ability of students 'vocabulary learning, and makes the learning diagnosis, resource recommendation and language application form a more stable collaborative relationship.

4.5 Analysis of System response Efficiency and deployment stability of Blended teaching Scene

In order to verify the feasibility of the deployment of the intelligent education platform in the blended teaching scenario, this paper sets the conditions of 50, 100, 150, 200 and 250 concurrent users to test the response delay of four types of core services: vocabulary resource retrieval, mastery status recognition, personalized recommendation generation and feedback update. The system response time delay variation under different concurrent loads is shown in Figure 8.

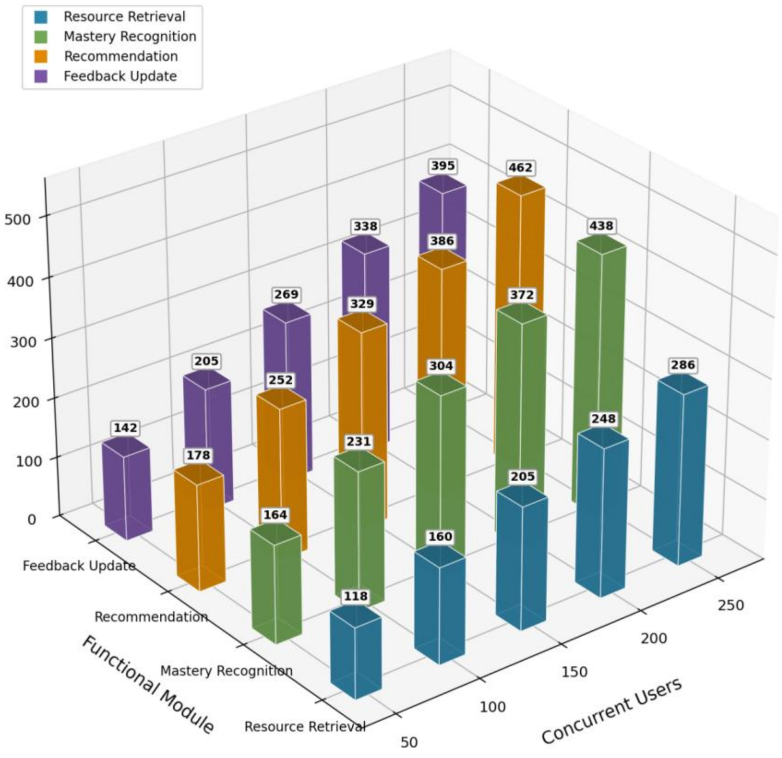

Figure 8: 3D bar graph of system response time delay under different concurrent loads

Figure 8 shows that with the increase of the number of concurrent users, the response delay of each functional module shows an upward trend, but the overall response delay is still in an acceptable range. The lexical resource retrieval module is supported by caching mechanism, and the latency increases from 118 ms under 50 concurrency to 286 ms under 250 concurrency, which increases slowly. The mastery state recognition module involved behavior sequence coding and graph feature fusion, and the delay was increased from 164 ms to 438 ms, which was a link with high computational pressure. The personalized recommendation generation module reaches 462 ms under 250 concurrency, the main reason is that candidate resource recall, score ranking and scene matching need to call state representation and graph services at the same time. The delay of feedback update module increased from 142 ms to 395 ms, showing good stability. On the whole, when there are no more than 200 concurrent users, the response delay of core services is less than 400 ms. Under the high load condition of 250 people, the platform can still maintain continuous operation without service interruption or request accumulation, indicating that the constructed platform has the real-time deployment ability to support the college English blended vocabulary teaching experiment.

4.6 Ablation experiment and effectiveness verification of personalized recommendation module

In order to further verify the contribution of each core module to the effect of personalized word recommendation, this paper takes the complete model as the benchmark, removes the vocabulary knowledge graph, mastery state recognition, application scenario features and feedback update modules respectively, and compares the changes of learning completion Rate, memory retention rate, vocabulary application score, NDCG and Hit Rate under different configurations. The results of ablation experiments are shown in Table 4.

Table 4: Comparison table of ablation experiment and personalized recommendation effect

Model Configuration	Learning Completion Rate / %	Retention Rate / %	Vocabulary Application Score / %	NDCG	Hit Rate
Without Vocabulary Knowledge Graph Module	87.6	82.4	80.7	0.781	0.806
Without Mastery State Recognition Module	85.9	80.8	79.5	0.762	0.788
Without Application Scenario Feature Module	88.3	83.1	81.9	0.795	0.817
Without Feedback Update Module	89.1	84.2	82.6	0.812	0.829
Full Model	93.1	88.5	87.4	0.867	0.884

As can be seen from Table 4, the complete model achieves the best results in all indicators. The learning completion Rate, memory retention rate and vocabulary application score reach 93.1%, 88.5% and 87.4% respectively, and the NDCG and Hit Rate reach 0.867 and 0.884 respectively. After removing the mastery status recognition module, the recommendation effect decreased most obviously, and the learning completion rate decreased to 85.9%, indicating that students 'vocabulary mastery status was the key basis for accurate matching of recommendation strategies. After removing the lexical knowledge graph module, the vocabulary application score decreased to 80.7%, indicating that word sense relationship, collocation relationship and task context association play an important supporting role in word transfer. After removing the application scenario features, the model can still complete the basic recommendation, but the adaptation between resources and reading, writing, and speaking tasks is weakened. After removing the feedback update module, all the metrics also decreased, indicating that dynamic feedback can continuously revise the recommendation priority. On the whole, the vocabulary knowledge graph, state recognition, scene adaptation and feedback update jointly ensure the stability and effectiveness of personalized recommendation.

5 Conclusion

Focusing on the personalized learning needs of blended vocabulary teaching in college English, this paper completes the integrated design of data collection, knowledge modeling, status recognition, resource recommendation and feedback update. In this study, the preview, test, review, reading, writing and speaking tasks are transformed into trainable event sequences, and the word knowledge graph is combined to depict the word meaning, collocation, context and task relationships, so that the deep learning model can identify the mastery state from the three dimensions of memory level, semantic understanding and application ability. The experimental results show that the Accuracy of the proposed model reaches 93.8%, and the F1-score reaches 92.9%. The learning completion Rate, memory retention rate and vocabulary application score of the complete recommendation model reach 93.1%, 88.5% and 87.4%, respectively, and the NDCG and Hit Rate reach 0.867 and 0.884. In the concurrent test, the platform maintained a stable response under the condition of 250 users. In the future, large language model feedback and cross-course transfer data can be introduced to improve the adaptive support ability in complex language tasks.

Funding

This work was supported by the College of Technology, Hubei Engineering University Teaching Reform Research Project (Grant No. 2024JY10).

References

[1] Lee, S. M. Factors affecting incidental L2 vocabulary acquisition and retention in a game-enhanced learning environment[J]. ReCALL, 2023, 35(3): 274-289. DOI: 10.1017/S0958344022000209.

[2] Dziemianko, A. The usefulness of graphic illustrations in online dictionaries[J]. ReCALL, 2022, 34(2): 218-234. DOI: 10.1017/S0958344021000264.

[3] Shahipanah, A., Khajavy, G. H., & Elahi Shirvan, M. The effect of textual and textual-pictorial glosses on incidental vocabulary learning in mobile-assisted listening[J]. ReCALL, 2025, 37(1): 79-95. DOI: 10.1017/S0958344024000193.

[4] Muñoz, C., Pattemore, A., & Avello, D. Exploring repeated captioning viewing as a way to promote vocabulary learning: Time lag between repetitions and learner factors[J]. Computer Assisted Language Learning, 2024, 37(7): 1744-1770. DOI:

10.1080/09588221.2022.2113898.

[5] Montero Perez, M. Second or foreign language learning through watching audio-visual input and the role of on-screen text[J]. Language Teaching, 2022, 55(2): 163-192. DOI: 10.1017/S0261444821000501.

[6] Soyoof, A., Reynolds, B. L., Shadiev, R., & Vazquez-Calvo, B. A mixed-methods study of the incidental acquisition of foreign language vocabulary and healthcare knowledge through serious game play[J]. Computer Assisted Language Learning, 2024, 37(1-2): 27-60. DOI: 10.1080/09588221.2021.2021242.

[7] Jeon, J. Chatbot-assisted dynamic assessment (CA-DA) for L2 vocabulary learning and diagnosis[J]. Computer Assisted Language Learning, 2023, 36(7): 1338-1364. DOI: 10.1080/09588221.2021.1987272.

[8] Jeon, J. Exploring AI chatbot affordances in the EFL classroom: Young learners' experiences and perspectives[J]. Computer Assisted Language Learning, 2024, 37(1-2): 1-26. DOI: 10.1080/09588221.2021.2021241.

[9] Uchihara, T. How does the test modality of weekly quizzes influence learning the spoken forms of second language vocabulary?[J]. TESOL Quarterly, 2023, 57(2): 595-617. DOI: 10.1002/tesq.3176.

[10] Gok, D., Bozoglan, H., & Bozoglan, B. Effects of online flipped classroom on foreign language classroom anxiety and reading anxiety[J]. Computer Assisted Language Learning, 2023, 36(4): 840-860. DOI: 10.1080/09588221.2021.1950191.

[11] Kim, H. S., Lee, J. H., & Lee, H. The relative effects of L1 and L2 glosses on L2 learning: A meta-analysis[J]. Language Teaching Research, 2024, 28(1): 7-28. DOI: 10.1177/1362168820981394.

[12] Serrano, R. Vocabulary learning from reading and listening: Replications of Brown et al. (2008) and Vidal (2011)[J]. Language Teaching, 2024, 57(1): 113-121. DOI: 10.1017/S0261444822000179.

[13] Calafato, R., & Clausen, T. Vocabulary learning strategies in extramural English gaming and their relationship with vocabulary knowledge[J]. Computer Assisted Language Learning, 2024: 1-19. DOI: 10.1080/09588221.2024.2328023.

[14] Serfaty, J., & Serrano, R. Practice makes perfect, but how much is necessary? The role of relearning in second language grammar acquisition[J]. Language Learning, 2024, 74(1): 218-248. DOI: 10.1111/lang.12585.

[15] Jeon, J. Exploring a self-directed interactive app for informal EFL learning: A self-determination theory perspective[J]. Education and Information Technologies, 2022, 27(4): 5767-5787. DOI: 10.1007/s10639-021-10839-y.

[16] Major, L., Francis, G. A., & Tsapali, M. The effectiveness of technology-supported personalised learning in low- and middle-income countries: A meta-analysis[J]. British Journal of Educational Technology, 2021, 52(5): 1935-1964. DOI: 10.1111/bjet.13116.

[17] Rodríguez-Martínez, J. A., González-Calero, J. A., del Olmo-Muñoz, J., Arnau, D., & Tirado-Olivares, S. Building personalised homework from a learning analytics based formative assessment: Effect on fifth-grade students' understanding of fractions[J]. British Journal of Educational Technology, 2023, 54(1): 76-97. DOI: 10.1111/bjet.13292.

[18] Drugova, E., Zhuravleva, I., Zakharova, U., & Latipov, A. Learning analytics driven improvements in learning design in higher education: A systematic literature review[J]. Journal of Computer Assisted Learning, 2024, 40(2): 510-524. DOI: 10.1111/jcal.12894.

[19] Heikkinen, S., Saqr, M., Malmberg, J., & Tedre, M. Supporting self-regulated learning with learning analytics interventions: A systematic literature review[J]. Education and Information Technologies, 2023, 28: 3059-3098. DOI: 10.1007/s10639-022-11281-4.

[20] Palanci, A., Yılmaz, R. M., & Turan, Z. Learning analytics in distance education: A systematic review study[J]. Education and Information Technologies, 2024, 29: 22629-22650. DOI: 10.1007/s10639-024-12737-5.

[21] Sghir, N., Adadi, A., & Lahmer, M. Recent advances in predictive learning analytics: A decade systematic review (2012-2022)[J]. Education and Information Technologies, 2023, 28: 8299-8333. DOI: 10.1007/s10639-022-11536-0.