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Development and Practice of an Intelligent Support System for English Collaborative Learning under the Project-based Learning Approach

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SUMMARY: *Currently, English project-based learning often presents phenomena such as "no goals" within the PBL framework, "lack of thinking" during the hands-on process, and "monotonous" evaluation forms, which are known as "shallow project-based learning". Grounded in PBL theory, the article combines Web service and database design methods to develop an intelligent support system for collaborative English learning. With the aim of deepening insight into students' English knowledge acquisition, the article combines the deep knowledge tracking model with graph neural network and establishes the DKT-GL model for English knowledge recommendation. On this basis, an English teaching practice based on the English collaborative learning intelligent support system was designed. It is found that the response time of the English collaborative learning intelligent support system is within 0.25s, and compared with the mainstream model, the DKT-GL model can help teachers better grasp students' comprehension of knowledge points. In English teaching practice, adopting the PBL approach can demonstrably enhance students' English spelling proficiency and capacity for autonomous learning. Devoting adequate attention to PBL methodology holds strong potential for elevating students' English knowledge acquisition and driving meaningful reform in English instruction.*

KEYWORDS: *project-based learning; Web services; system development; DKT-GL model; deep knowledge tracking*

1 Introduction

The PBL approach represents a learner-centered instructional strategy that immerses students in complex, authentic problem contexts, encouraging them to pursue solutions through self-directed inquiry and collaborative effort, thereby fostering both knowledge acquisition and capability development [1-4]. Different from traditional teaching methods, the project-based learning method is no longer a one-way transmission of knowledge by the teacher on the podium and passive acceptance by the students [5, 6]. Rather, students learn around a specific project that usually simulates an actual task or problem in the real world [7]. Under this approach, by developing an intelligent support system for collaborative English learning and applying it to teaching practice serves as a meaningful contributor to enhancing the overall standard of English instruction.

With the development and progress of the world, the function of English has become more and more prominent. Under the requirements of this era, China has been exploring the teaching of English and carrying out a series of curriculum reforms, from the traditional classroom lectures and teaching of grammar and vocabulary knowledge to the transformation of student-

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oriented collaborative learning, which has achieved remarkable results [8-11]. And English collaborative learning intelligent support system is the combination of collaborative learning and computer-assisted teaching based on the gradual development of a multidisciplinary domain encompassing artificial intelligence, computer science, cognitive science, pedagogy, psychology and behavioral sciences, but also a prominent area of inquiry within educational technology [12-15]. By intelligently adapting English teaching resources and refining both the collaboration process and evaluation feedback, the system holds considerable capacity to strengthen the outcomes of project-based English collaborative learning, carrying substantial practical significance [16, 17].

This study aims to develop an intelligent support system for English collaborative learning under the project-based learning method, and to carry out practical teaching in combination with teaching experiments. Combining project-based learning, Web services and database technology, we designed an intelligent support system for English collaborative learning and introduced deep knowledge tracking, graph neural network, LSTM and attention mechanism, etc., and constructed a DKT-GL model for grasping students' understanding of English knowledge points. Then the sixth grade students of an elementary school in Y city of C province were used as the research sample to start the teaching experiment. This study provides a novel avenue for advancing intelligent support systems in English collaborative learning, a fresh approach to driving innovation in English instructional practice models, and an original lens through which to enhance the standard of English instruction and boost learners' English competence.

2 Intelligent Support System for English Collaborative Learning Grounded in PBL

PBL in practice of practical application, the need to take the constructivist learning theory as an important guiding ideology, mainly to guide the students can be in a more realistic problematic situation for learning activities, but also able to enhance the student's diversified learning mode to a certain extent. Based on the PBL theory, the English collaborative learning intelligent support system is established by combining various types of system development technologies, which in turn promotes the reform of English teaching.

2.1 Project-based learning theory and process

2.1.1 Theoretical underpinnings of project-based learning

PBL prioritizes the cultivation of student competencies, with instruction organized around well-defined learning objectives; throughout this process, the teacher's role in the classroom is no longer a single classroom manager, but a guide for students' independent learning. Not only the overall teaching more prominent to learners as the central participants, at the same time, including cooperative learning method, situational learning method, including some of the new teaching methods can also be fully integrated application. In addition, throughout the PBL process, the project theme selected by the teacher can be both a task and a problem, which means that students can obtain more obvious learning effects as long as they follow the steps of conceptualization, verification, improvement and solution under the guidance of the teacher. Not only can effectively avoid the problem of low participation in learning that existed in the past indoctrination mode of teaching, but also make the classroom teaching objectives clearer, which helps to form a good order of classroom teaching, and in this way promotes the significant improvement of students' learning efficiency.

In project-based learning, constructivist learning theory, multiple intelligence learning theory and lifelong development learning theory is the main theoretical basis, and these theories emphasize the learning process to play the learner's sense of independent learning, which makes the students to continue to obtain the knowledge they deserve through the independent construction of the knowledge system. This is completely different from the traditional educational ideas focusing on teacher indoctrination, which is in line with the modern educational concept of innovation and practical ability training requirements. Teachers in the project-based teaching process, more like a student learning facilitator, in the more loose course plan to offer students a broad orientation for guidance, so as to support students in bringing their projects to successful completion.

2.1.2 Project-based learning application process

PBL represents a learner-driven instructional format. In the practice of English teaching, teachers design learning projects for students in a reasonable way, drive students to think independently and investigate cooperatively with projects, fully activate students' intrinsic motivation in learning, and nurture students' core competencies within the English discipline. Figure 1 illustrates the implementation process of the PBL approach, encompassing the clarification of PBL content, further innovation of PBL forms, reinforcement of PBL guidance, and optimization of PBL evaluation.

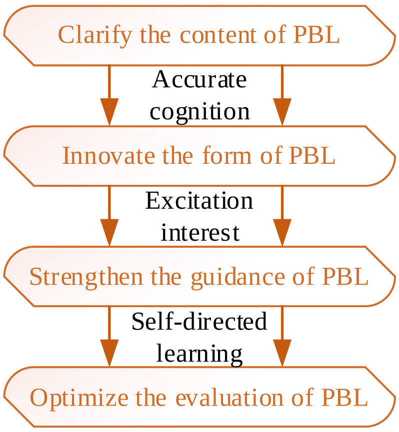

Figure 1: PBL implementation process

(1) Define the content of project-based learning. English teachers should change their teaching thinking, pay attention to the students' main position, and reasonably set the content of PBL.

(2) Innovate the form of PBL. English teachers should take into account students' learning ability level, learning interest and learning habits, and design interactive and interesting learning forms.

(3) Strengthen the guidance of project-based learning. English teachers should fully leverage their mentoring role in students' learning and development, and make students think deeply and think effectively with the help of effective guidance, so as to promote the successful completion of PBL tasks.

(4) Optimize the evaluation of PBL. English teachers should pay attention to refining and enhancing the PBL assessment approach, through the development of diversified evaluation, comprehensive evaluation and guidance on the learning process and learning results.

2.2 Project Learning System Development Design

2.2.1 Web services framework

The traditional Web system architecture is a client/server (C/S) mode two-layer design mode, this mode can use the client and server side of their respective hardware advantages, the completion of the task to achieve the appropriate division, to reduce the communication load of the system. But the swift expansion of the Internet has exposed various vulnerabilities in the C/S architecture; in order to meet the system easy to use, easy to expand, easy to maintain and other characteristics, the B/S architecture is proposed to achieve the sharing of system resources. At present, the lightweight J2EE platform occupies an absolute advantage in system development, which mainly includes four-layer architecture of client layer, representation layer, business logic tier and information system tier.

The J2EE four-tier structure is implemented via the MVC model. Given the specific focus of this study, JSP+Servlet+JavaBean technology is adopted in constructing the English collaborative learning intelligent support system, which provides a research platform for analyzing the application of English PBL, and then promotes the innovation of English teaching.

2.2.2 Database design methodology

The data design in this study uses an E-R model-based data architecture approach, which is a widely used tool for data modeling in system database design. The E-R model is applied during the conceptual design stage of a system to capture the information requirements and categorize the types of data to be stored in the database.

In the E-R model, entities are objects or concepts that are related to the business in the system, and these entities can be identified by rectangular boxes in which the name of the entity or the name of the object is written. Each entity has a set of attributes which are represented by elliptical boxes with the attribute name written inside the box and connected to the entity rectangular box with undirected edges. A link among entities is depicted using a diamond-shaped box carrying a descriptive label, with the rectangular boxes of entities involved in the linkage are each connected to the diamond box, and the linkage lines are labeled with the type of linkage, e.g., 1-to-1, 1-to-n, or n-to-n. These connections can represent different business needs, such as teacher-to-student connections or teacher-to-class connections. By using the E-R model, it can help developers better understand the business requirements and design a high-quality and reliable database system. At the same time, the E-R model can also provide guidance for the establishment of business rules to ensure data integrity, consistency and accuracy.

2.2.3 English collaborative learning support system

Supported by PBL theory, combined with Web service technology and database design methodology, this paper designs the English Collaborative Learning Intelligence Support (ECLIS) system, the framework of which is shown in Fig. 2.The English Collaborative Learning Intelligence Support System supported by Web services should provide management support, learning resources support, collaborative communication support, and results display and evaluation support for the development of English project learning.

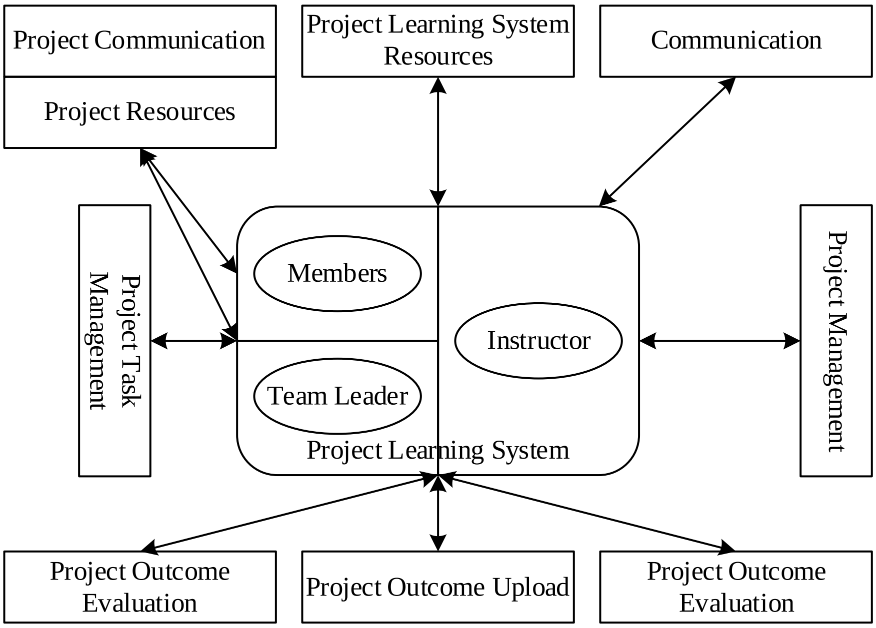

Figure 2: English Collaborative Learning Intelligent Support system

The Project Learning System realizes the management of projects as well as the management of project teams in the Project Management module. Teachers create projects, set project start and stop, add project team members, and designate project team leaders in the project management module. In the project learning system, the project team members' online learning resources are added by the project team leader from the resource library of the project learning system that can be used to assist the completion of the project, which avoids the project members from going to study indiscriminately in the huge learning resources, and makes the learners' learning more targeted. Learners may choose the learning resources suitable for them according to their own learning styles. The online communication module of the project learning system mainly realizes the information exchange between the learners and teachers and learners in the process of project learning, and the information exchange makes the learners more self-confident and makes the learners know how to think differently.

2.3 English Collaborative Learning System Test

2.3.1 System performance test results

Software testing is a necessary part for guaranteeing stable system functioning, through software testing can largely reduce the probability of errors, and effectively control the development costs. In this paper, the system performance test, the test environment is mainly in the following configuration of the machine for the test, the operating system is Ubuntu 20.00.4 LTS, memory and hard disk for 16GB and 1TB, respectively, the processor is i3-10300.

Performance evaluation constitutes a critical phase in software development, and the system undergoes performance testing to verify software stability. The English Collaborative Learning Intelligent Support System serves as a multi-user platform handling large volumes of simultaneous access; to validate system stability, performance assessments were carried out across several system modules. A stress test was conducted replicating a scenario of 1000 concurrent users accessing the course learning module. Figure 3 presents the performance test results for the course learning module as a representative example, illustrating requests per second, responses per second, and average latency across the three measured indicators in sequence. The findings confirm that the system exhibits short response times, maintains stable overall operation, with all response times falling within 0.25s.

As revealed by the data distribution presented in the figure, the trend curves for requests per second and responses per second align closely, suggesting that the gap between request and response is minimal. Further examination of the average latency confirms that delays remain negligible, with all course learning modules operating within 250ms free of errors or timeouts, thereby satisfying the deployment requirements of the English Collaborative Learning Intelligent Support System.

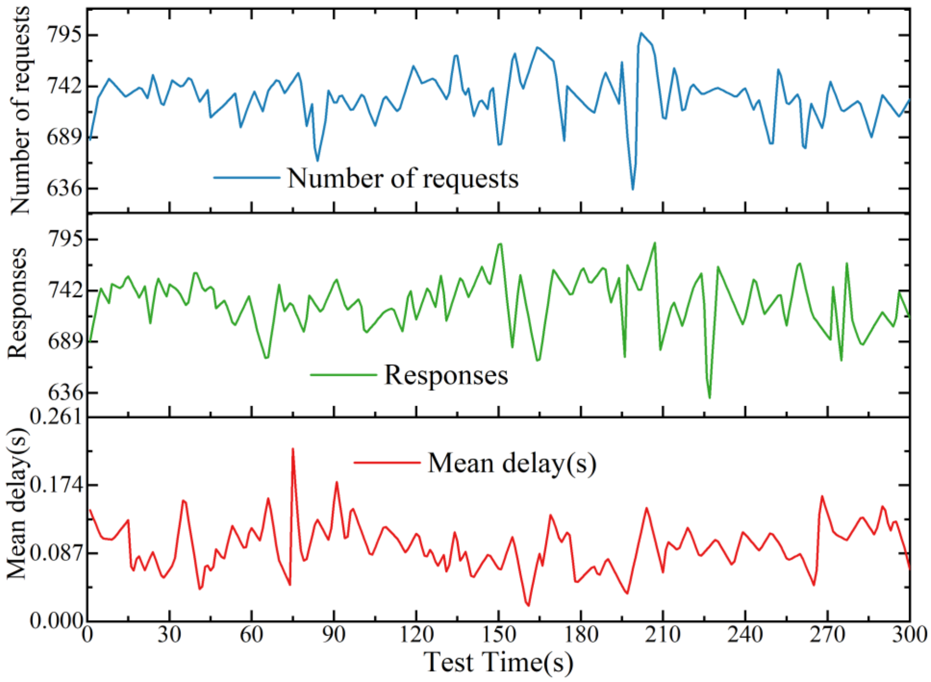

Figure 3: Performance test performance chart

2.3.2 Multi-task metric completion rate

With the aim of assessing the overall performance of the ECLIS system in handling multitasking metrics computation during collaborative English language learning, a comparative experiment was carried out on the system. Heterogeneous Hybrid Cloud Service (HMCS) system and Multi-core System Task Scheduling (MSTS) system are used to implement the comparison test, 600 English teaching tasks are randomly run on different systems, and the three systems are taken to compare the time-consuming metrics for English teaching multitasking calculations, and the results of time-consuming test for English teaching task calculations on different systems are obtained as shown in Figure 4.

Analyzing the data in the figure, it is found that the mean value of the processing overhead of the ECLIS system developed in the present study is 3.14s for 600 English teaching tasks, and the mean value of the computational effort of the HMCS system and the MSTS system for English teaching multitasks is 5.55s and 7.61s, which is 76.75% and 142.36% higher than the ECLIS system designed in this paper, respectively. As a result, the ECLIS system in this paper has the best overall ELT task metrics time-consuming performance, which verifies that the ECLIS system has the best ELT multi-tasking metrics. This is because the ECLIS system is based on PBL theory, combined with JSP+Servlet+JavaBean technology and E-R model to extract the data of ELT multitasking, which in turn improves the efficiency of ELT multitasking metrics.

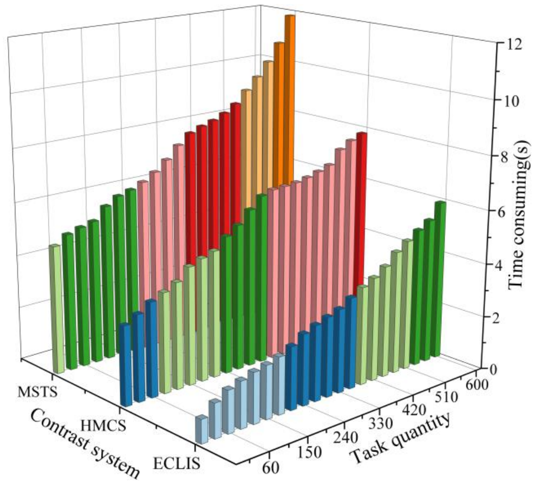

Figure 4: Task calculation force measurement time-consuming testing

A large amount of English teaching task data information is further selected and analyzed to obtain the 600 task data that need to be measured in the system, from which the task model is constructed, from which a task data is obtained, defined as TF1 ≤ GXZC, where TF1 denotes the task data, and GXZC denotes the type of task. On this basis, the English teaching multi-tasking metric completion rates of different systems are calculated, followed by the comparison results as shown in Figure 5.

As observable from the figure, when evaluating English teaching task data, the task metric completion rate achieved by the ECLIS system developed in this study ranks highest, reaching an average of 89.75%, while the task metrics of the remaining systems fall considerably short of those of the present study's ECLIS system, with the mean values of the task metric completion rates of the HMCS system and the MSTS system being 76.14% and 67.12%, respectively. This demonstrates that the ECLIS system developed in this study achieves superior task measurement completion outcomes, which is due to the fact that the ECLIS system implements the labeling and quantification of English teaching tasks, which in turn enhances the measurement effect of the ECLIS system and improves the multi-task measurement completion rate.

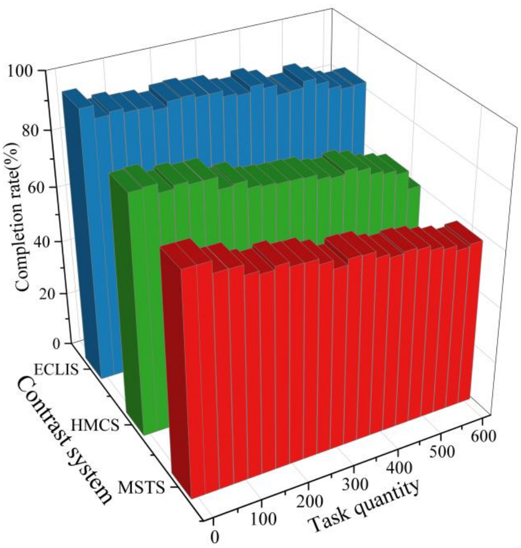

Figure 5: Multitask measurement completion ratio test

3 English Knowledge Recommendation Model Based on Knowledge Tracing

Under the English collaborative learning intelligent support system supported by project-based learning, deep learning technology can be introduced to assist English teachers to understand students' knowledge mastery, so as to better recommend knowledge recommendation results suitable for students' knowledge status, and to provide support for ensuring the quality of English teaching and improving students' English literacy and so on.

3.1 DKT model and graph neural network

3.1.1 Deep knowledge tracing

Deep Knowledge Tracking (DKT) centers on capturing the learner's knowledge mastery state via recurrent neural networks. Compared to the Bayesian Knowledge Tracking (BKT) model, DKT achieves no manual labeling of the dataset and achieves better results than other models.

In DKT model, x_t denotes the input vector of the input layer, the hidden layer state is jointly shaped by the preceding hidden state h_{t-1} and the current input vector x_t, while the output layer y_t produces the predicted probability of a correct response to the question. The DKT model is formulated as follows::

$$h_t = \tanh\left(W_{hx}x_t + W_{hh}h_{t-1} + b_h\right) \tag{1}$$

$$y_t = \sigma\left(W_{yh}h_t + b_y\right) \tag{2}$$

where W_{hx} is the input weight matrix, b_h is the hidden layer bias, W_{hh} is the recursive weight matrix, σ is the Sigmoid function, W_{yh} is the output weight matrix, and b_y is the output layer bias.

3.1.2 Graph Neural Networks

A graph can be defined as $G = \{V, E, W\}$, where V denotes the set of nodes of the graph with the number of nodes $|V| = N$, E denotes the edges connecting the nodes in the graph, and W denotes the graph adjacency matrix containing the connectivity between any two nodes in V. The elements of the i th row and j th column in W can be denoted by w_{ij}, which represents the importance of the connection between the i th node and the j th node. The task of graph classification refers to the use of a graph's adjacency matrix and feature data to derive the mapping between the graph and its corresponding category labels, subsequently inferring the labels of unseen graphs through machine learning. To accurately classify a graph, the available structural and node feature information must be comprehensively exploited.

Graph Neural Networks (GNNs) have become a major technical tool across data mining and analytical domains owing to their good interpretability, and their core idea is to enhance the model's representational capability through message propagation mechanism and optimize the node representations through downstream tasks. Its formalization is described as:

$$h_v = f\left(x_v, x_{co[v]}, h_{ne[v]}, x_{ne[v]}\right) \quad o_v = g\left(h_v, x_v\right) \tag{3}$$

where f serves as the local transformation operator, g acts as the local output operator, and $x_v, x_{co[v]}, h_{ne[v]}, x_{ne[v]}$ represent the node features, edge features, neighbor node states,

3.2 DKT-GL model framework design

3.2.1 Modeling Framework and Graph Embedding

With the aim of more accurately capturing students' English knowledge mastery, so as to recommend English knowledge that is more in line with their knowledge level, this paper establishes the DKT-GL model by combining the deep knowledge tracking model, graph neural network, and the attention mechanism, etc., and its specific architecture is depicted in Fig. 6. The model comprises three components, namely graph embedding module, student knowledge state characterization module and prediction module. First, the graph embedding module enhances the problem features according to the problem-knowledge point relationship, generates the embedded representations of the problem and knowledge points through the problem-knowledge point relationship graph G, and improves the node feature representation capability through the comparison probability optimization. Then, the extraction capability of the model for long-term dependencies between sequences is enhanced by the student knowledge state characterization module and the problem matching module to further enhance the problem features. In particular, the student knowledge state characterization module generates learner knowledge states derived from the problem features. Finally, the prediction module calculates the probability that a student can correctly answer the predicted question.

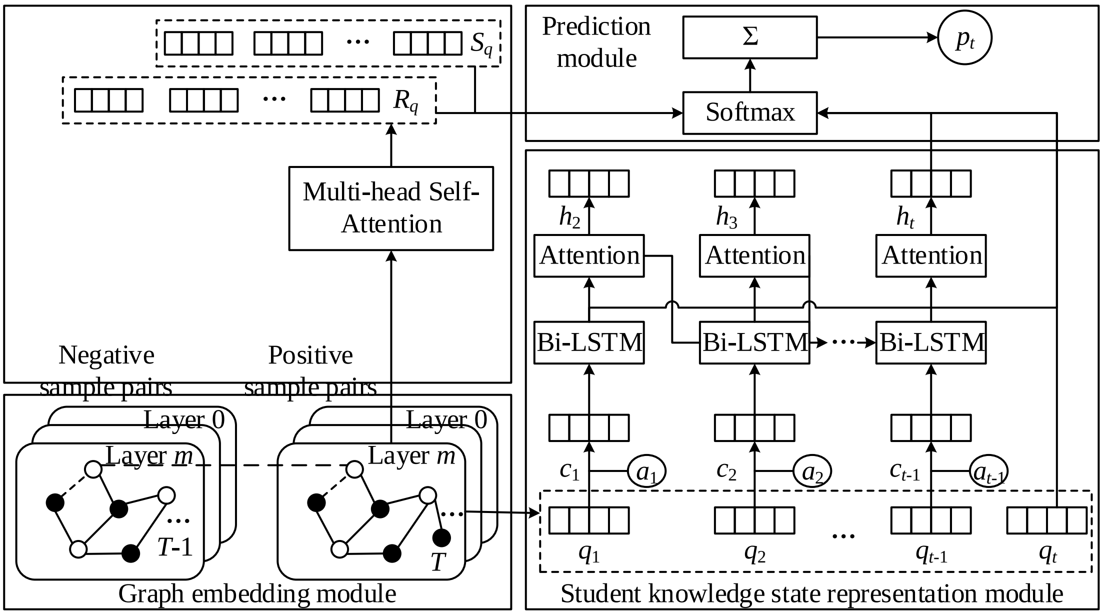

Figure 6: Model architecture of DKT-GL

In order to extract problem features more accurately, modeling problem features needs to consider the relationship between problems and knowledge points, and modeling is based on the problem-knowledge point relationship graph. The property of graph neural networks to capture higher-order associative information in graph-structured data by aggregating the information of neighboring nodes is just right for modeling the relationship between questions and knowledge points in the relational graph G. Therefore, the module uses a GCN encoder to generate node embedded representations in the question-knowledge point relationship graph consisting of students' historical answer records. Two matrices are used in the GCN propagation process, a question-question relationship matrix and a question-knowledge point relationship matrix, where the neighbors of a question are other questions answered by that student and the knowledge points associated with that question, and the neighbors of a knowledge point are the exercises associated with it.

The GCN has many graph convolutional layers to encode higher-order neighbor information, and the nodes in each layer can be updated by the states of their own and neighboring nodes. Denoting the representation of node i in the graph as α_i (α_i can denote either a problem embedding or a knowledge point embedding), and the set of its neighboring nodes as $\mathcal{N}_i$, the node representation of the l th GCN layer is:

$$\alpha_i = \mathrm{Re}\,LU\left(\frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i\cup\{i\}} W^l\alpha_j^{l-1} + b^l\right) \tag{4}$$

where W^l and b^l are the aggregation weights and offsets in the l th layer of the GCN.

3.2.2 Characterization of the state of student knowledge

The Long Short-Term Memory (LSTM) network represents a specialized variant of the Recurrent Neural Network (RNN), retaining the core characteristics of RNN while addressing its limitation in handling long-term dependency problems.

In this paper, we use LSTM to simulate the knowledge growth state of students by converting the input sequences $v_1', v_2', \ldots, v_t'$ into hidden knowledge states $h_1, h_2, \cdots, h_t$ through the LSTM network. . At moment t, the LSTM computes the unit state of the network according to the following formula.

The input gate i_t is first used to determine what new information needs to be added to the nearest neuron state c_t. Using h_{t-1}, v_t', and a sigmoid function, a selection is made of which information in the memory cell to update. After that, the information of the cells to be selected c_t is obtained through h_{t-1}, v_t', and a tanh function. The procedure is as follows:

$$i_t = \sigma\left(W_i\left[v_t', h_{t-1}\right] + b_i\right) \tag{5}$$

$$\tilde{c}_t = \tanh\left(W_c\left[v_t', h_{t-1}\right] + b_c\right) \tag{6}$$

In addition to this, the ratio of forgotten and retained old cell information is determined by the forgetting gate f_t when updating the new cell information. Combining the old cell data filtered by the forgetting gate and the candidate input data produced by the input gate, the updated cell state c_t is derived. The computation proceeds as follows:

$$f_t = \sigma\left(W_f\left[v_t', h_{t-1}\right] + b_f\right) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{8}$$

Subsequently, the output gate o_t determines which information will be extracted from c_t to constitute the hidden state h_t, i.e., based on h_{t-1}, v_t', and the sigmoid function:

$$o_t = \sigma\left(W_o\left[v_t', h_{t-1}\right] + b_o\right) \tag{9}$$

$$h_t = o_t \odot \tanh(c_t) \tag{10}$$

in which W and b denote the trainable weight matrix and bias vector.

3.2.3 Attention Mechanisms and Prediction

The interrelationships among exercises completed by students exert an influence on their knowledge acquisition states, which is captured through an exponential index decay scheme embedded in the attention mechanism. The initial attention query matrix and key-value pair are formulated as follows:

$$Q_1 = EW^{q_1}; K_1 = I_G W^{k_1}; V_1 = I_G W^{v_1} \tag{11}$$

where W^{q_1}, W^{k_1} and W^{v_1} are trainable parameter matrices designed to capture the influence of prior practice problems on the current practice problem. In addition, an exponential decay term is introduced to obtain higher weights at shorter distances. The attentional weight computation is expressed as:

$$A\left(Q_1, K_1, V_1\right) = Soft\max\left(\frac{Q_1 K_1^T}{\sqrt{d}} B\right) V_1 \tag{12}$$

For B, multiply each of the corresponding terms by an exponential term β^{t-j}, where $i \geq j, \beta < 1$. The Softmax term is computed specifically as follows:

$$s_{ij} = \frac{q_i^T k_j}{\sqrt{d}} \cdot \beta^{t-j} \tag{13}$$

The foregoing describes a single attention matrix; to extract richer information from the data, this study employs multiple attention matrices through a multi-head attention mechanism, expressed as:

$$U_1 = c\left(W_{head_1}, \ldots, W_{head_h}\right) W_1^o \tag{14}$$

where $W_{head_i} = A\left(Q_1^i, K_1^i, V_1^i\right)$, c denotes a matrix concatenation operation accompanied by a parameter matrix $W_1^o \in \mathbb{R}^{h \times d \times d}$, $U_1 \in \mathbb{R}^{n \times d}$.

With the aim of more effectively capturing the influence of students' historical exercises on their current performance, this study feeds E_G as Q into the attention mechanism. The second attention computation query matrix and key-value pair are formulated as:

$$Q_2 = E_G W^{q_2}; K_2 = U_1 W^{k_2}; V_2 = U_1 W^{v_2} \tag{15}$$

where W^{q_2} , W^{k_2} and W^{v_2} are trainable parameter matrices. The attentional weight computation is expressed as:

$$A(Q_2, K_2, V_2) = Soft\max\left(\frac{Q_2 K_2^T}{\sqrt{d}} B\right) V_2 \tag{16}$$

The long attention computation is given by:

$$U_2 = c\left(W_{head_1^2}, \ldots, W_{head_h^2}\right) W_2^o \tag{17}$$

where $W_{head_i^2} = A\left(Q_2^i, K_2^i, V_2^i\right)$; parameter matrix $W_2^o \in \mathbb{R}^{h \times d \times d}$; $U_2 \in \mathbb{R}^{n \times d}$. The U_2 produced by the attention mechanism encodes the students' current level of knowledge concept mastery, and is subsequently passed forward into the next layer of the network structure.

The student's knowledge point mastery characteristic $U_2 \in \mathbb{R}^{n \times d}$ is taken as input. Specifically, the input $U_2^T = (m_1, m_2, \ldots, m_n)$, $m_i \in \mathbb{R}^{d \times 1}$ is obtained by convolution of $H^c = \left(h_1^c, h_2^c, \ldots, h_{n+k-1}^c\right) \in \mathbb{R}^{d \times (n+k-1)}$, where:

$$h_i^c = \operatorname{Re}lu\left(\sum_{j=1}^{d} G \times \left(m_{i+k-1}^j, m_{i+k-2}^j, \ldots, m_i^j\right)^T + b\right) \tag{18}$$

where $G \in \mathbb{R}^{d \times k}$,denotes a dd d-dimensional convolution kernel of length k , m_i^j refers to the j th dimensional element of m_i , $b \in \mathbb{R}^{d \times 1}$ is the function bias term, and $\operatorname{Re}lu = \max(0, x)$ is the activation function. In order to facilitate the operation of the model, the first n dimensions are taken in this study, i.e., the output of this layer is $H^c \in \mathbb{R}^{d \times n}$.

The H^c after causal convolution is fed into an activation layer through which the student's performance is predicted as follows:

$$p_i = Sigmoid\left(\left(H^c\right)^T W^o\right) \tag{19}$$

where p_i denotes the likelihood of a student responding correctly to a given question, $W^o \in \mathbb{R}^{d \times N}$, N represents the total count of questions and $Sigmoid(Z) = 1/(1+e^{-Z})$.

3.3 DKT-GL model performance validation

3.3.1 Comparative analysis of model performance

This study conducts experiments on two authentic online education datasets to assess the effectiveness of the DKT-GL model by benchmarking its predictive performance against other knowledge tracing models. The real online education datasets selected for this paper include Assistment2012 and Assistment2018, for which 70% of the data in the dataset is randomly allocated to the training set and the remaining 30% to the test set, with evaluation conducted via ten-fold cross-validation.

To assess the DKT-GL model's effectiveness, AUC and ACC serve as the evaluation metrics for benchmarking model performance; generally, an AUC or ACC value of 0.5 reflects performance equivalent to random guessing, with higher values of both metrics indicating stronger predictive power. The DKT-GL model represents a knowledge tracing framework that jointly incorporates the learning process and learning behaviors, with key hyperparameters set as follows: embedding layer dimensions of 256, hidden layer dimension of 512, number of attention heads of 10, and query, key and value vector mapping dimension of 256. Table 1 presents the performance comparison of the model across different datasets.

The results show that the DKT-GL model outperforms the other compared methods on both datasets. Compared with DKT-GL, DKT and SAKT have poorer prediction results, which indicates that only considering only the knowledge point mastery (Stu-C) has limited improvement on the model performance. Meanwhile, the DKT-GL model, which incorporates all three interaction types within the learning process, improves about 1.59% in the evaluation metric AUC than the suboptimal model AKT, which only takes into account the interactions between Stu-C and knowledge points and exercises (C-E), which proves that the interactions between the students and the exercises considered in PBKT serve a significant function in enhancing model performance.

On both datasets, the AUC of the DKT-GL model reached 0.829 and 0.765 respectively, representing an improvement of approximately 1.59% over the sub-optimal model. This indicates that the DKT-GL model has good performance in multiple application scenarios. Combining the experimental results, we can see that the DKT-GL model achieves better results by integrating the learning process and learning behavior. This will help us better grasp the cognitive states of learners and elevate both the standard and effectiveness of personalized English education.

Table 1: Performance comparison of models on different data

Model	Assistment2012		Assistment2018	
	ACC	AUC	ACC	AUC
IRT	0.678	0.674	0.665	0.684
FBKT	0.632	0.645	0.629	0.568
PFA	0.715	0.712	0.654	0.646
DAS3H	0.724	0.739	0.692	0.715
DKT	0.758	0.705	0.691	0.727
SAINT	0.734	0.743	0.654	0.609
SAKT	0.709	0.738	0.686	0.705
GKT	0.714	0.712	0.679	0.684
PEBE-DKT	0.763	0.814	0.683	0.732
AKT	0.762	0.816	0.714	0.753
DKT-GL	**0.768**	**0.829**	**0.721**	**0.765**

3.3.2 Analysis of knowledge acquisition

Applying the DKT-GL model in the English collaborative learning intelligent support system can determine the students' knowledge mastery level based on their doing big data. In this study, the results of the model are categorized according to three levels, with a probability of 0.4 or less signifying insufficient knowledge point mastery, a probability between 0.4 and 0.8 reflecting a moderate level of mastery, and a probability of 0.8 or more reflecting a high level of mastery. Furthermore, this section concentrates on examining the DKT-GL model output with respect to students' overall English knowledge mastery and inter-group variation in knowledge mastery.

In the article, two classes of students (120 students) in the sixth grade of an elementary school in Y city were chosen as the experimental subjects, and their learning data were collected and used as inputs to be analyzed in conjunction with the DKT-GL model, following which the students' knowledge mastery of English was obtained as presented in Fig. 7. Based on the figure, regarding the overall English knowledge mastery of the 120 students, the number of students at a low level (mastery level less than 0.4) totaled 14, comprising 11.67% of the total student cohort. The number of students with good and good levels of English knowledge mastery was 71 and 35 respectively. On the whole, the students have a high level of mastery of English textbook knowledge. English Knowledge Mastery For some of the students with poor level, teachers can carry out personalized tutoring to strengthen their mastery of the basic content. In addition, a large part of the students have a good level, and the teachers can strengthen their ability of transformation and application to help them further improve. For some of the relatively weak students, attention should be paid to personalized tutoring to help them improve their knowledge mastery.

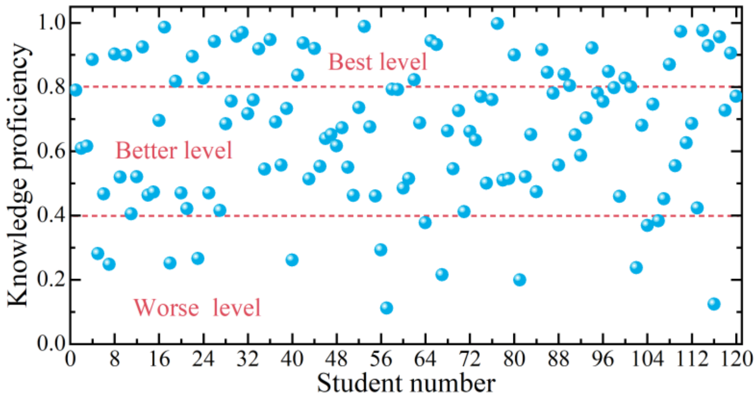

Figure 7: Mastery of English knowledge

The group differences are mainly brought about by the knowledge acquisition of students of different genders. In terms of gender, there are a total of 67 and 53 boys and girls respectively who took the quiz. For the English knowledge situation, this paper is divided into a total of six different types of knowledge points (KP1~KP6), based on the DKT-GL model to compare the mastery of English knowledge points under different genders. Figure 8 shows the differences in English knowledge point mastery across genders.

As can be seen from the figure, in the boys' group, more than 80% of the boys mastered English knowledge points 1 and 2, of which the proportion of mastering KP1 reached 100%, and in the girls' group, more than 80% of the girls mastered KP1, 2, 3, 5 and 6. It can be found through the comparison of the data in the figure that the proportion of the girls' group's mastery of each knowledge point is higher than that of the boys', which means that as a whole, the girls in the mastery of English knowledge points performed better than boys.

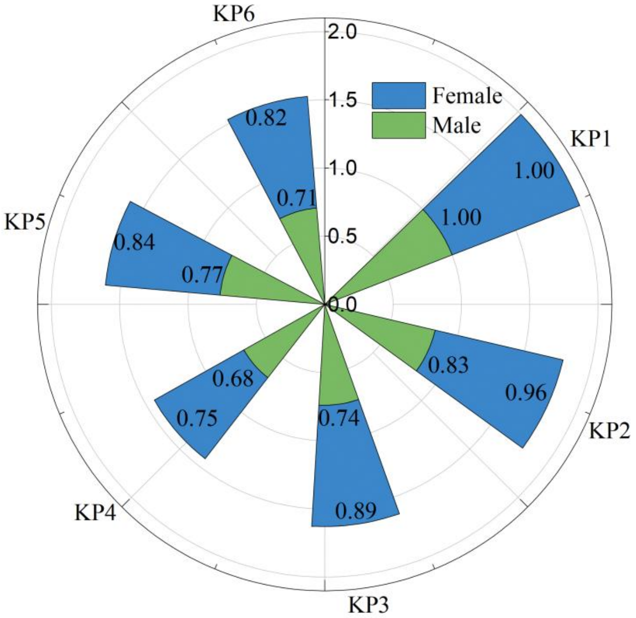

Figure 8: Different gender English knowledge points are different

4 English Teaching Practices Based on Intelligent Support System

Project-based learning is learning through the completion of projects closely related to real life, and is a practical activity that fully selects and makes use of optimal learning resources, acquires more complete and specific knowledge, forms specialized skills and develops in practical experience, internalization and absorption, and exploration and innovation. PBL encourages learners to engage with authentic real-world problems, and throughout the problem-solving process, not only fosters students' creative thinking, but also develops their spirit of inquiry.

4.1 Research Design for Teaching English as a Second Language (TEFL) Practice

4.1.1 Selection of research subjects

In this study, two parallel classes in the sixth grade of an elementary school in Y city, C province were selected as samples. Sixty students from each class were chosen to participate in the experiment with participant ages spanning from 12 to 14 years old. The first class served as the experimental group and the second as the control group. In this paper, project-based learning English teaching, i.e., teaching using English collaborative learning intelligent support system, will be conducted in the experimental class, and regular English teaching will be conducted in the control group. The academic environments of the students across both groups are relatively consistent, the students in both classes are randomly assigned to classes, and the class teachers and subject teachers are relatively stable. From the English final quality test of the first semester of Grade 6, the English level of the two cohorts is comparable. The students in both groups had already received more than three years of school English education, had a certain foundation in English, and had a high interest in learning English.

After a thorough literature study, a four-month teaching experiment was started. Among them, September to October 2024 was the preliminary assessment phase of the teaching experiment, October to December 2024 was the stage of comparing the teaching experiment between the experimental class and the control class, January 2025 was the concluding assessment phase of the teaching experiment, and January to February 2025 was the stage of analyzing and organizing the data and discussing them.

4.1.2 Questionnaire design

The questionnaire survey is composed of two components: pre-test and post-test, both surveys were conducted in the experimental class, and in response to what was learned, this paper designs its own questionnaire, which consists of five aspects. It mainly includes five dimensions of English independent learning ability encompassing goals, plans, strategies, monitoring and evaluation, and learning process (ZX1~ZX5).

The pre- and post-tests of the questionnaire used similar questionnaires to facilitate comparative testing, and the purpose of the questionnaire was to want to understand the challenges encountered in English learning and learners' familiarity with the PBL approach. To further assess whether the PBL method, as reflected in pre- and post-test data shifts, exerts a beneficial influence on the development of students' autonomous English learning capacity, all participants were invited to complete the questionnaire items based on their actual circumstances.

Responses were scored on a five-point Likert scale, where 1 to 5 correspond respectively to strongly agree, agree, neutral, disagree, and strongly disagree. The questionnaire has passed the reliability and validity test, indicating that the instrument demonstrates strong reliability and structural validity.

4.2 Analysis of Data on English Teaching Practices

4.2.1 Comparison of students' spelling skills

Given that PBL teaching delivered through the English collaborative learning intelligent support system yields a notable impact on students' spelling proficiency, and with the aim of examining the extent of this effect across different student abilities, the participants were divided into an experimental group (EG) and a control group (CG), and independent samples t-tests were performed on the outcomes. Table 2 presents the pre- and post-experiment performance comparison with respect to students' English spelling ability.

It can be found that prior to the experiment, no substantial performance gap existed between the experimental group and the control group, with the experimental group scoring only 0.26 points above the control group on the whole. Following the experiment, we found that

the experimental group recorded a considerably greater improvement, reaching an overall score of 46.59 points, while the control group's performance remained steady at approximately 35.37 points, representing a notably wider gap. This suggests that, setting aside the influence of external factors, PBL teaching delivered through the English collaborative learning intelligent support system exerts a substantially stronger effect on the enhancement of students' spelling proficiency. Through the independent samples t-test we found that the overall sample spelling scores of the data in the pre-experimental test did not change significantly, and the significance reached 0.634 greater than 0.05, so the original hypothesis is rejected. We concluded that the spelling scores of the control group exhibited no meaningful variation before and after the condition without the English collaborative learning intelligent support system. But in the post-experimental data control we found that the data before and after a more significant change, the significance of the post-test is 0.001 less than 0.05, so the original hypothesis is accepted, we believe that the English collaborative learning intelligent support system before and after the two groups of achievement test comparison of spelling scores have a more significant difference, that is, the project-based learning method is more significant impact on spelling scores, through the control analysis found that The English teaching supported by the English collaborative learning intelligent support system affects students' spelling ability more.

Table 2: Comparison of English spelling ability

Test	Group	N	Means	STD	STEM
Before	EG	60	34.21	2.812	0.571
	CG	60	33.95	2.657	0.548
After	EG	60	46.59	2.743	0.526
	CG	60	35.37	4.582	0.935
T test of the mean equation					
Group	*t*	Sig.(2-tailed)	Difference	95% CI Lower	95% CI Upper
Before	0.527	0.634	0.26	-1.163	2.047
After	0.349	0.001	11.22	1.015	5.792

4.2.2 Comparison of students' spelling skills

PBL teaching grounded in the English collaborative learning intelligent support system exerts a meaningful effect on students' spelling proficiency, and to quantify the magnitude of this effect, the outcomes of the experimental and control groups were benchmarked against each other using independent samples t-tests. Table 3 presents the pre- and post-experiment score comparison for students' English spelling ability.

As revealed by the tabulated data, the mean pre-experiment spelling scores of the experimental group and the control group stood at 36.57 and 36.72 respectively, yielding a mean difference of only 0.15, which constitutes a negligible gap. And the independent samples t-test Sig. value is 0.516 (greater than 0.05), confirming that the two groups demonstrated essentially equivalent spelling proficiency prior to the experiment with no statistically meaningful difference,and it is suitable for conducting the experiment. After four months of study and consolidation, the average scores of the postexperimental spelling ability test recorded by the experimental group and the control group upon conclusion of the experiment stood at 48.15 and 38.96 respectively, reflecting a mean score gap of 9.19 points. The independent samples t-test yielded a Sig. value of 0.000 (less than 0.05), confirming a statistically significant divergence in English spelling scores between the two groups following the experiment.

Table 3: Comparison of English spelling ability

Test	Group	N	Means	STD	STEM
Before	EG	60	36.57	1.973	0.282
	CG	60	36.72	2.051	0.343
After	EG	60	48.15	2.126	0.374
	CG	60	38.96	0.251	0.417
T test of the mean equation					
Group	*t*	Sig.(2-tailed)	Difference	95% CI Lower	95% CI Upper
Before	0.174	0.516	0.15	-5.127	4.231
After	18.421	0.000	9.19	0.572	1.468

4.2.3 Self-directed learning skills in English

With the aim of examining the influence of implementing PBL through the Intelligent Support System for Collaborative English Learning on students' autonomous English learning capacity, this study administered a questionnaire on English independent learning ability to the research participants both prior to the commencement of the action research and upon completion of the two rounds of action research.

Five dimensions were organized and discussed in this study, i.e., five aspects of students' English independent learning ability in terms of goals, planning, strategies, monitoring and evaluation, and learning process. This study used SPSS data analysis software to conduct descriptive statistical analysis on the pre- and post-test data of the English Independent Learning Ability Questionnaire. Table 4 presents an overview of students' English independent learning ability.

As the table reveals, the mean value of the pre-intervention questionnaire on the first and second dimensions is only slightly above 3 points, between "average (3 points)" and "compliant (4 points)", while the mean value on the third, fourth and fifth dimensions is less than 3 points, between "does not meet (2 points)" and "average (3 points)". The mean values of the latter questionnaire on all dimensions were between "average (3 points)" and "more in line (4 points)", and the post-intervention questionnaire yielded higher mean scores than the pre-intervention questionnaire across all dimensions. This indicates that following the adoption of PBL through the English collaborative learning intelligent support system, students' autonomous English learning capacity underwent meaningful shifts across the five dimensions of goals, plans, strategies, monitoring and evaluation, and the learning process; accordingly, this study concludes that PBL implementation exerts a constructive influence on students' English independent learning ability, and it is considered that project-based learning is conducive to stimulating the students' learning initiative and enhance students' independent learning ability.

Table 4: Overall situation of autonomous English learning ability

-	Means		Standard deviation		Average standard error	
	Before	After	Before	After	Before	After
ZX1	3.043	4.258	0.603	0.643	0.082	0.086
ZX2	3.015	4.121	0.845	0.768	0.115	0.104
ZX3	2.724	3.509	0.743	0.756	0.094	0.095
ZX4	2.836	3.792	0.617	0.618	0.082	0.083
ZX5	2.767	4.015	0.624	0.647	0.083	0.084

Table 5 presents the paired samples t-test outcomes for students' English independent learning ability. The bilateral Sig. values for the pre- and post-test data across each questionnaire dimension all fall below 0.01, attaining significance at the 1% level. This leads to the conclusion that meaningful differences exist between the pre- and post-intervention scores of students' autonomous English learning capacity following the two rounds of action research, demonstrating that students' English independent learning ability has undergone improvement over the course of PBL instruction.

Table 5: Paired samples: t-test outcomes

Pair	Difference value	Standard deviation	95% CI		t	Sig.(2-tailed)
			Lower	Upper		
Pair 1	-1.215	0.492	-0.462	-0.203	-5.715	0.001
Pair 2	-1.106	0.603	-0.573	-0.252	-6.334	0.000
Pair 3	-0.785	0.791	-0.604	-0.174	-5.251	0.002
Pair 4	-0.956	0.774	-0.634	-0.216	-4.273	0.000
Pair 5	-1.248	0.782	-0.668	-0.243	-4.562	0.000

5 Conclusion

The article establishes an English collaborative learning intelligent support system under the project-based learning method, designs an English knowledge recommendation model based on knowledge tracking, and designs an English teaching practice experiment. It is found that the response time of the English collaborative learning intelligent support system is short (0.25s) and the overall operation is stable, and the DKT-GL model has better prediction ability than the mainstream model, which can effectively analyze students' mastery of English knowledge points. Relying on the English collaborative learning intelligent support system to carry out English teaching, it can significantly enhance students' English spelling ability, spelling ability and independent learning ability, and provide a direction to promote the reform of English education.

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