International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 2489-2503

https://doi.org/10.70517/ijhsa464210

A Study on Strategies for Optimizing the Development of Classroom Interaction Skills Among English Teacher Education Students in an English Teaching Environment Based on an Adaptive Learning System

Qiaoli He[1] and Jing Zeng[1,*]
[1] Xiangnan University, Chenzhou, Hunan, 423000, China
Corresponding authors: (e-mail: jean19882024@163.com).

Abstract This paper integrates LSTM networks and attention mechanisms to construct a deep knowledge tracking model based on feature embedding and attention mechanisms, and evaluates the predictive performance of this model. A university English intelligent adaptive learning system is designed, and the characteristics of teacher-student speech behavior and teacher-student interaction in English classrooms are analyzed, with corresponding optimization strategies proposed. DKT-FA achieved prediction accuracies of 0.8402, 0.8821, 0.7506, and 0.7976 on the ASSISTment2009, ASSISTment2017, EdNet, and English datasets, respectively, achieving the best performance among all tested models. In Lesson Example 1 (an English teaching classroom based on an adaptive learning system), the teacher speech ratio, student speech ratio, teacher direct influence ratio, teacher indirect influence ratio, student active response rate, and student passive response ratio were 49.5%, 34.6%, 38.3%, 11.2%, 4.4%, and 24.2%, respectively. Case 2 (traditional teaching method) had the following ratios: 58.4%, 17.3%, 45.5%, 12.9%, 3.5%, and 7.6%. In Case 2, teacher speech behavior was concentrated in the first half and exceeded student speech behavior. In Case 1, teacher speech behavior was more balanced, and teacher-student interaction frequency was more stable.

Index Terms adaptive learning, deep knowledge tracking, iFIAS, English teaching, interaction ability

I. Introduction

In English classrooms, teacher-student interaction is crucial, as it promotes student learning outcomes, enhances mutual trust between teachers and students, and facilitates emotional communication [1], [2]. As demonstrated in Reference [3], which examined the impact of interactive teaching methods on college students' learning outcomes, the application of interactive teaching methods helps improve students' critical thinking, collaborative skills, and self-efficacy. Additionally, positive teacher-student interaction can stimulate students' interest in learning, increase their motivation, and also help teachers better understand students' learning situations and needs, thereby enabling more targeted instruction [4]-[6]. Literature [7] studied the impact of interactive learning strategies on students' interest in learning and verified through interviews and observations that interactive learning strategies can effectively enhance students' interest in learning, though there are some obstacles, such as insufficient infrastructure.

In teacher-student interactions, students can more actively ask questions and engage in interactive exchanges with teachers and peers, thereby deepening their understanding and mastery of knowledge [8], [9]. Literature [10] analyzed the role of interactive strategies in improving English language acquisition, emphasizing that interactive strategies, as a common teaching strategy, play an important role in enhancing the effectiveness of English classroom instruction. Teacher-student interactions also enable students to better apply learned knowledge, improving their language expression and communication skills [11]. Literature [12] aims to identify the types of interaction between teachers and students in the classroom. Based on observational and interview methods, it points out that teacher-student interaction primarily manifests in the transmission of materials, teacher discourse, and student expression of ideas.

The importance of teacher-student interaction in English classrooms is self-evident, especially for English education students. It serves as a crucial pathway for promoting learning, expanding thinking, and broadening horizons, playing an indispensable role in the future success of their English teaching careers [13]-[16]. Literature [17] analyzed the role of interactive teaching methods in English instruction, particularly in enhancing language proficiency, promoting active participation, and fostering cultural understanding. It also validated the effectiveness of this method in cultivating critical thinking and promoting personalized learning experiences. However, in current

English teacher education, under traditional teaching models and methods, students lack classroom interaction skills, have low motivation, and fail to create an active classroom atmosphere, resulting in ineffective teaching outcomes. Enhancing English teacher education students' classroom interaction abilities has become a critical focus for higher education institutions [18]-[21]. Literature [22] describes the efforts teachers have made to achieve classroom interaction, pointing out the challenges faced in achieving this goal, especially students' lack of cooperation, and emphasizing that the absence of interactive teaching severely hinders the improvement of teaching quality.

In recent years, with the rapid development of digital technology, adaptive learning systems have been widely applied in the field of education, particularly in English teaching. The design and research of adaptive learning systems have become a focal point for educators, providing technical support for developing the interactive abilities of English teacher education students [23]-[26]. Literature [27] introduces the application of adaptive learning systems in higher education, emphasizing the reasons for their growing attention, namely their ability to provide personalized learning trajectories and enhance students' learning outcomes. Literature [28] examines the application of artificial intelligence in English teaching and evaluates the functions of adaptive tools, emphasizing that artificial intelligence tools are an effective supplementary teaching option, particularly in adaptive learning, as they can meet students' learning needs and improve learning outcomes.

Adaptive teaching systems are a personalized teaching method based on individual student differences. They achieve targeted teaching and improve learning outcomes by automatically adjusting teaching content and strategies according to students' needs and abilities [29]-[31]. Literature [32] explores the effectiveness of adaptive learning systems in personalized teaching and analyzes the impact of personalized learning on student academic performance. Based on a literature review, it reveals the effectiveness of personalized learning in improving learning outcomes and the challenges faced in its implementation. Literature [33] investigates the architecture, benefits, and challenges of AI-driven adaptive learning technologies, analyzing key algorithms, learning models, and their applications in various educational settings, demonstrating the significant potential of adaptive learning systems in improving educational outcomes.

In English language instruction, adaptive teaching systems can effectively address students' learning needs by optimizing the English learning environment and providing personalized learning experiences, thereby fostering the development of effective classroom interaction skills [34]-[37]. Literature [38] aims to design and develop an innovative AI-assisted multilingual adaptive learning system. This system, based on AI algorithms, provides dynamic and personalized learning experiences tailored to students' individual learning levels and styles, thereby enhancing learning outcomes. Literature [39] highlights the transformative impact of adaptive learning systems on English education, noting that the personalized learning experiences they offer meet students' individual needs, enhance their learning experiences, and address the shortcomings of traditional methods.

This paper integrates an attention mechanism into a knowledge tracking model, combining student response behavior characteristics, question difficulty coefficients, and other features to construct a deep knowledge tracking model (DKT-FA). It uses LSTM to simulate students' knowledge growth states, combining a soft attention mechanism with LSTM to enable the model's attention to focus more on similar behavioral characteristics and question difficulty. Subsequently, the DKT-FA model undergoes experimental testing to evaluate its predictive accuracy in knowledge tracking tasks, thereby validating its effectiveness. Based on this, an English intelligent adaptive learning system is designed, and the language behavior characteristics of teachers and students, as well as classroom interaction patterns, are studied across different English lesson scenarios. Finally, feasible optimization recommendations are proposed in response to the current situation.

II. Deep knowledge tracking model based on feature embedding and attention mechanism

II. A.Basis for improvement

This paper first addresses the issue of limited input data by embedding students' answering behavior characteristics and exercise difficulty coefficients. Second, in students' historical answering records, past answering results to some extent influence their current knowledge mastery. To address this issue, this paper introduces an attention mechanism into the knowledge tracking model, performing weighted aggregation calculations on all historical information to reduce the loss of important information.

Based on the above two points, this paper proposes a deep knowledge tracking model DKT-FA based on feature embedding and attention mechanisms. The overall framework of the model is shown in Figure 1.

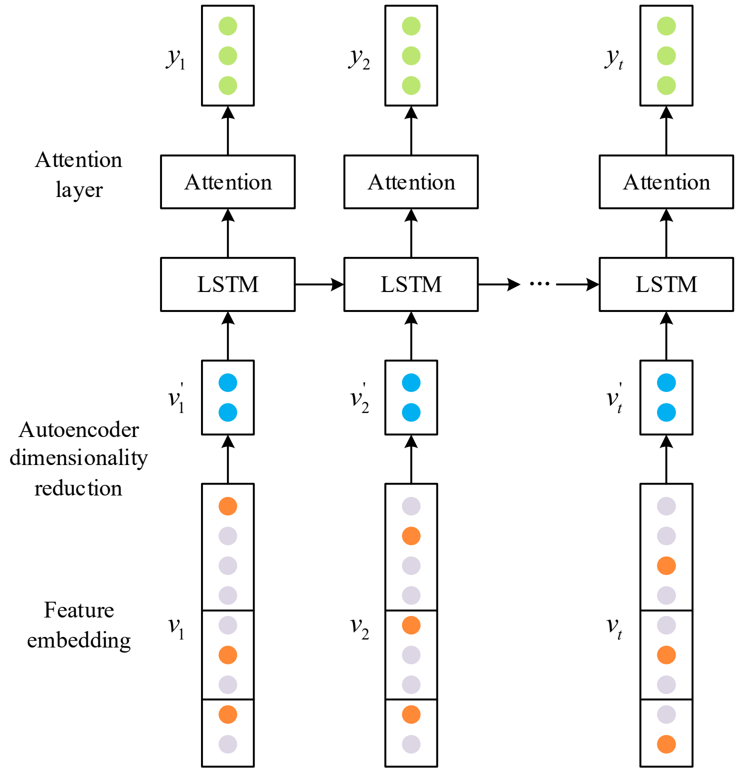

Figure 1: DKT-FA model frame diagram

II. B.Problem Definition

Knowledge tracking predicts whether students can answer the next question correctly by assessing their mastery of knowledge points [40]. Knowledge tracking problems are typically described as follows: given a set of historical interaction sequences $x_1,\cdots,x_t$ for a student during a certain time period, predict their performance on the next question. Generally, $x_t=\{q_t,a_t\}$, where q_t represents the knowledge point corresponding to the question answered, and a_t represents whether the answer is correct, typically $a_t=\{0,1\}$, where 0 indicates an incorrect answer and 1 indicates a correct answer.

Based on the above discussion, this chapter expands the input data information of the model by embedding both the student's answering behavior features and the question difficulty coefficient into the original input information x_t, transforming x_t into a more meaningful historical interaction sequence v_t'. Therefore, the input to the knowledge tracking model in this chapter is the historical interaction sequence $V'=(v_1',v_2',\cdots\cdots,v_t')$, and the output is the probability vector predicting the questions corresponding to the knowledge points answered correctly by the student.

II. C.Input layer

II. C. 1) Characteristics of students' answering behavior

During the problem-solving process, students typically exhibit three types of learning behaviors identified by time series: the number of times a student attempts to answer a question, whether assistance is requested during the problem-solving process, and the number of times hints are requested. This paper proposes a novel feature interaction method that combines the three types of problem-solving behavior features into a new feature and performs feature interaction with the problem-solving results, as shown in Equations (1) and (2). Where ac_t represents the number of times a student attempts to answer a question at time t, fa_t indicates whether assistance was requested, hc_t denotes the number of times hints were requested, and a_t signifies the answer result. That is:

$$C(f_t,a_t)=f_t+(\max(f)+1)\cdot a_t C(f_t,a_t)=f_t+(\max(f)+1)\cdot a_t \tag{1}$$

$$f_t=ac_t+fa_t+hc_t \tag{2}$$

Among these, fa takes the values 0 and 1, where 0 indicates that the student did not request assistance when answering the question at time t, and 1 indicates that the student relied on external assistance to answer the question at time t. The number of attempts to answer the question ac and the number of times assistance was requested hc are both represented by natural numbers. To ensure the reasonableness of the sum of the three features, any values greater than 2 in ac and hc are represented by 2. The new student answering behavior features can be obtained by directly summing the previous features, without considering the order of processing between them.

II. C. 2) Question Difficulty Coefficient

This section uses a difficulty coefficient calculation method to calculate the difficulty of the question and embeds the calculation results into the model's input data. The difficulty coefficient is generally represented by D and the formula is shown in (3):

$$D_i = \frac{m_i}{N_i} \tag{3}$$

In this context, m_i denotes the number of students who answered question i incorrectly, and N_i denotes the total number of students who answered question i. The difficulty coefficient calculated using the above formula ranges from 0 to 1, with a smaller coefficient indicating a simpler question. For convenience of discussion, this paper divides the difficulty coefficient into 10 levels, i.e., $c = 10$. When the number of students answering a particular question in the answer records is too small, the difficulty coefficient level for that question is set to 5, as shown in formula (4):

$$Difficulty(i) = \begin{cases} \lfloor D_i \cdot c \rfloor & if\ |N_i| \geq 4 \\ 5 & else \end{cases} \tag{4}$$

II. C. 3) Feature Embedding Improves DKT Input Layer

This paper incorporates the new student answering behavior characteristics mentioned above and important additional information such as the quantified question difficulty coefficient into the original input data of DKT as new input data.

To improve the accuracy of the model, the knowledge points and answering behavior characteristics are cross-referenced with the answering results. All the encoded characteristics obtained are connected to form the input vector as shown in Figure 2.

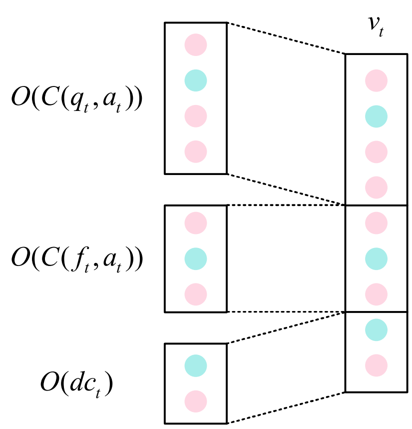

Figure 2: Input vector construction diagram

q_t denotes the knowledge point number, a_t denotes the answer result, f_t is the combination of student answer behavior characteristics, and dc_t is the difficulty coefficient of the current question. The vector construction process is shown in Equations (5) and (6):

$$C(q_t, a_t) = q + (max(q) + 1) \cdot a_t \tag{5}$$

$$v_t = O(C(q_t, a_t)) \cap 0(C(f_t, a_t)) \cap 0(dc_t) \tag{6}$$

Among them, $C()$ is the feature combination, $O()$ is the one-hot encoding format, and the $\cap$ operator is used to represent concatenation.

An autoencoder is essentially a multi-layer neural network. Like other neural networks, autoencoders use gradient descent to train parameter weights.

The autoencoder is trained using the tanh activation function. After training, the output layer is removed, and the output of the hidden layer is directly used as the input for the DKT-FA model, as shown in Formula (7). In our experiments, the output size of the hidden layer is reduced to half of the input size, i.e., the combined features of v_t are transformed into v_t' with half the dimension:

$$v_t' = \tanh(W \cdot v_t + b) \tag{7}$$

II. D.LSTM Layer

This paper uses LSTM to simulate the knowledge growth status of students [41], converting the input sequence v_1', $v_2', \cdots, v_t'$ into hidden knowledge states $h_1, h_2, \cdots, h_t$ through the LSTM network. At time t, the LSTM calculates the network's cell state according to the following formula.

First, the input gate i_t determines which new information needs to be added to the recent neuron state c_t. Using h_{t-1}, v_t' and a sigmoid function, it selects which information in the memory cell to update. Then, using h_{t-1}, v_t' and a tanh function, the selected cell information $\tilde{c}_t$ is obtained. The specific process is shown in Equations (8) and (9):

$$i_t = \sigma(W_i[v_t', h_{t-1}] + b_i) \tag{8}$$

$$\tilde{c}_t = \tanh(W_c[v_t', h_{t-1}] + b_c) \tag{9}$$

In addition, when updating new cell information, the proportion of old cell information to be forgotten and retained must be determined through the forgetting gate f_t. Combining the old cell information processed by the forgetting gate with the input information obtained by the input gate, the current cell state c_t is obtained. The specific process is shown in Equations (10) and (11):

$$f_t = \sigma(W_f[v_t', h_{t-1}] + b_f) \tag{10}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{11}$$

Finally, the output gate o_t determines which information to extract from c_t to form the hidden state h_t based on h_{t-1}, v_t' and the sigmoid function, as shown in equations (12) and (13):

$$o_t = \sigma(W_o[v_t', h_{t-1}] + b_o) \tag{12}$$

$$h_t = o_t \odot \tanh(c_t) \tag{13}$$

Among them, W and b are the learned weight matrix and bias vector.

II. E. Attention Layer

Attention mechanisms are categorized into two types: soft attention mechanisms and hard attention mechanisms [42]. This paper employs a soft attention mechanism. By utilizing an LSTM network, the hidden learning state of a student at each time step can be obtained, with the student's current learning state corresponding to the final hidden state of the LSTM network. This section proposes integrating the attention mechanism into a deep knowledge tracking model to prevent the loss of important information. By combining the attention mechanism with LSTM, the model focuses more attention on answer sequences with similar behavioral features and exercise difficulty.

The mathematical representation of the above process is given below. First, the model uses the attention variable $z(z \in [1, t-1])$ to indicate the index position of the information being focused on, where $z = i$ indicates that the i th answer record is selected. The probability of the i th input information is calculated using historical sequence information encoding and the last-time information encoding. The calculation formula is shown in (14):

$$\begin{aligned} \alpha_i &= p(z = i \mid V', v_t') \\ &= soft\max(s(v_i', v_t')) \\ &= \frac{\exp(s(v_i', v_t'))}{\sum_{j=1}^{t} \exp(s(v_j', v_t'))} \end{aligned} \tag{14}$$

Among these, the weighting factor α determines which parts should be given priority attention and which parts should be ignored during prediction. The function $s(v_i', v_t')$ is the attention score function, which includes four different calculation methods: additive model, dot product model, scaled dot product model, and bilinear model. In this experiment, the additive model is used to calculate the attention score, as shown in Formula (15):

$$s(v_i', v_t') = \tilde{v}^T \tanh(W_1 v_i' + W_2 v_t') \tag{15}$$

Among them, v_i' is the encoded representation of the reduced-dimensional historical sequence information, v_t' is the encoded representation of the reduced-dimensional input information at time t, and W and $\tilde{v}$ are learnable network parameters. The attention state s_t is represented as the weighted sum of H, and the calculation formula is shown in (16):

$$s_t = \sum_{j=1}^{t} \alpha_j h_j \tag{16}$$

Finally, combine h_t and s_t and use formula (17) to predict the probability of students mastering all knowledge points:

$$y_t = \sigma(W(s_t \oplus h_t) + b) \tag{17}$$

The training objective of the model is to reduce the error between the predicted answer results and the actual answer results through training, thereby obtaining a probability of student knowledge point mastery that is closer to the actual situation, and predicting the student's answer situation at the next moment through probability. This paper uses cross-entropy as the loss function of the DKT-FA model, as shown in Formula (18):

$$L = -\sum_{t} (a_{t+1} \log(y_t^{T} \delta(q_{t+1})) + (1 - a_{t+1}) \log(1 - y_t^{T} \delta(q_{t+1}))) \tag{18}$$

II. F. Experimental Results and Analysis

In this section, comparative experiments will be conducted on three publicly available mainstream datasets for knowledge tracking tasks and a real-world dataset constructed based on an online education platform. Additionally, to validate the scientific validity and effectiveness of feature selection, experimental analyses were conducted on multiple features of the model embedding interface. Two popular error metrics were used to measure prediction accuracy: prediction accuracy (ACC) and area under the ROC curve (AUC), where higher ACC or AUC values indicate higher accuracy.

II. F. 1) Introduction to the dataset

Three publicly available online education datasets—ASSISTment2009, ASSISTment2017, and EdNet—and a real-world dataset named English, constructed based on the Future Education Online Platform, were selected for experimentation. The statistical data are shown in Table 1.

(1) ASSISTment2009: From the ASSISTMENTS online tutoring system, after removing duplicate records, it contains 320,651 interactions across 125 skills involving 4,252 students.

(2) ASSISTment2017: After removing interactions without named skills, it ultimately contains 924,766 interactions across 117 skills for 1,853 students.

(3) EdNet: This is a large knowledge tracking public dataset. To avoid time-consuming training, 12,000 students' practice sequences were randomly sampled, and experiments were conducted on this subset.

(4) English: This is an English subject dataset from the online education platform College English Test, reflecting students' actual learning conditions. A random sample of 33,264 interactions across 632 different questions from 550 students was extracted, with the data comprising results from multiple comprehensive tests and multiple unit tests.

Table 1: Introduction of experimental dataset

Dataset	Students	Questions	KCs	Responses
ASSISTment2009	4252	16574	125	320651
ASSISTment2017	1853	3265	117	924766
EdNet	12000	12485	1854	1157482
English	550	632	63	33264

II. F. 2) Experimental setup

For all datasets, 20% is used as the test set, 20% as the validation set, and the remainder as the training set. All parameters in model training are determined using an automated network search method on the validation set to identify optimal parameters, with the learning rate candidate range being: {10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}}, the candidate range for dropout is: {0.05, 0.1, 0.15, 0.2, 0.25, 0.3}, the candidate range for batch size is: {16, 32, 64, 128, 256, 512}, The candidate ranges for all embedding dimensions and the hidden state dimensions in LSTM and GRU are: {32, 64, 128, 256, 512}. Ultimately, all embedding dimensions and the hidden state dimensions in LSTM and GRU were set to 256, dropout was set to 0.2, batch size was set to 32, and the learning rate was set to 0.0001.

II. F. 3) Student Performance Prediction

The model presented in this paper was implemented alongside seven comparison models, including three knowledge tracking models based on MFAKT embeddings and five baseline models. To ensure fairness in the experiments, all models were adjusted to achieve optimal performance. The comparison models include DKT, DKT+, SAKT, DKVMN, SKVMN, SAINT, and AKT. The average AUC and average ACC from 5-fold cross-validation experiments were used as comparison results, with baseline model results derived from reproducing the original open-source code.

The experimental results of each model on the dataset are shown in Table 2. As shown in Table 2, DKT-FA outperforms all other baselines across all datasets. Specifically, DKT-FA performs at least 1% better than other models, demonstrating the model's effectiveness. Notably, DKT-FA significantly outperforms other models on the ASSISTment2017 dataset, showing an improvement of at least 2.5%. This is because the ASSISTment2017 dataset has the highest average response density per student, and DKT-FA can effectively capture long-range dependencies in sequence. In general, AKT and DKT-FA significantly outperform other models, which can be attributed to the effective utilization of problem information and related skills. Compared to AKT, DKT-FA uses a more information-rich question representation and employs LSTM to model forgetting behavior, which contributes to its superior performance.

SAKT performs the worst across all datasets in all deep models, as it uses learnable positional embeddings and does not explicitly model forgetting behavior, thereby failing to learn effective positional representations in these datasets.

Table 2: Experimental results of each model in the dataset

Model	ASSISTment2009		ASSISTment2017		EdNet		English	
	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC
DKT	0.8478	0.7603	0.7407	0.6734	0.7155	0.6867	0.8269	0.7524
DKT+	0.8554	0.7806	0.7723	0.6818	0.7519	0.7004	0.8091	0.7536
SAKT	0.8075	0.7558	0.7239	0.6696	0.7241	0.6798	0.8009	0.7428
DKVMN	0.8755	0.7694	0.7987	0.7391	0.7477	0.7176	0.8057	0.7545
SKVMN	0.8779	0.7586	0.8213	0.7466	0.7617	0.6959	0.8207	0.7597
SAINT	0.8409	0.7721	0.8663	0.7799	0.7782	0.6975	0.8254	0.7612
AKT	0.8721	0.8175	0.8881	0.8437	0.7968	0.7149	0.8338	0.7665
DKT-FA	0.9065	0.8402	0.9102	0.8821	0.8155	0.7506	0.8598	0.7976

II. F. 4) Ablation experiment

To further validate the effectiveness of the different modules of the proposed model, DKT-FA was compared with the following variants: DKT-KE, DKT-EQE, DKT-PE, DKT-RC, and DKT-RAF. The results of the ablation study are shown in Table 3.

DKT-FA achieved the best performance among all models, demonstrating the effectiveness of its different components. DKT-KE performed the worst among all variants of DKT-FA, but it still outperformed deep models that only use skills as input, such as DKT, DKVMN, and SAKT. This indicates that problem information plays a significant role and can greatly enhance model performance. DKT-FA outperforms DKT-EQE on all datasets, particularly on ASSIST2009 and ASSIST2017, reflecting that the multi-feature embedding method is more effective than the problem embedding based on the Rasch model used in AKT. DKT-FA outperforms DKT-PE on all datasets, highlighting the necessity of positional information, especially on ASSIST2009, which demonstrates the effectiveness of the sequence encoding layer in DKT-FA. From DKT-RC, it can be observed that some contextual information is ignored by the self-attention layer, leading to performance degradation, thereby demonstrating the effectiveness of the contextual layer. DKT-FA outperforms DKT-RAF on most datasets, indicating that the fusion gate proposed by DKT-FA can adaptively learn feature weights, controlling the information that should be retained by the two latent features.

Table 3: Ablation experiment results

Models	ASSIST2009	ASSIST2017	EdNet	English
DKT-KE	0.8865	0.8326	0.7623	0.8234
DKT-EQE	0.8975	0.8679	0.8157	0.8356
DKT-PE	0.9012	0.8775	0.8163	0.8364
DKT-RC	0.8986	0.8693	0.8142	0.8457

DKT-RAF	0.9186	0.8762	0.8132	0.8538
DKT-FA	0.9175	0.9072	0.8206	0.8607

III. Design of an English intelligent adaptive learning system based on iFIAS

III. A. Design of an Intelligent Adaptive Learning System for University English

There is no universally accepted definition of the components of an intelligent adaptive learning system, but it typically includes at least three parts: a structural model of the content to be learned (content model), methods for assessing students' abilities (learner model), and methods for matching content and presenting it to learners in a dynamic and personalized manner (instructional model). Based on this, the author designed an intelligent adaptive learning system for university English, as shown in Figure 3.

As shown in Figure 3, first, we establish a resource repository based on the learning content of university English textbooks, including a question bank compiled from the textbook content and supplementary learning materials of comparable difficulty. Second, students enter the system to learn, and their learning behaviors are recorded by the system. Then, through deep knowledge modeling, data analysis is conducted to obtain the learner model, which represents the learner's knowledge state and knowledge structure. Subsequently, the instructional model combines the learner model and content model to identify learning materials that match the learner's knowledge level and delivers them to students in a personalized manner. Additionally, it provides learning path planning, learning strategy recommendations, teacher learning interventions, and collaborative learning support, thereby achieving personalized learning for students. This process, in turn, provides support for the construction of the university English resource repository, continuously improving and refining it.

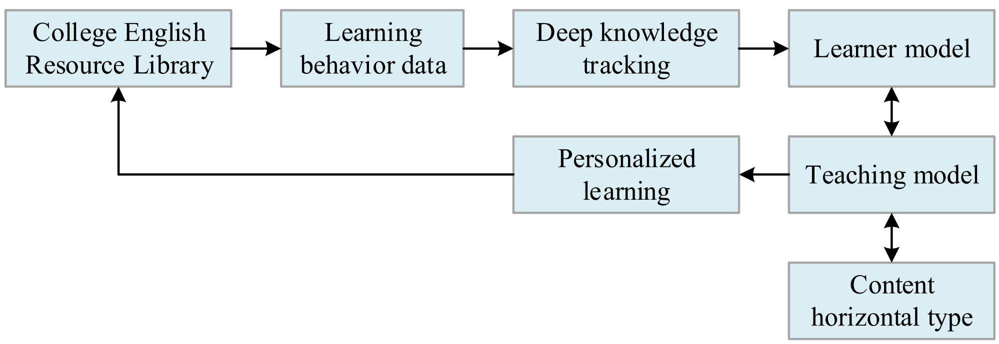

Figure 3: The basic framework of the college English intelligent adaptation learning system

From the perspective of learning task design in the university English resource repository, it is recommended to adopt the task-based teaching method. This approach emphasizes “learning by doing” rather than mechanical drills of language knowledge, enabling the form and meaning of language to be unified in authentic communicative tasks. This allows language to truly achieve communicative purposes, helps students internalize language knowledge more effectively, and enhances their language application skills. Specifically, when designing learning tasks, factors such as the authenticity of learning materials, student interaction with learning materials, and collaboration with peers should be considered.

From the perspective of learning environment design in the university English resource repository, it is recommended to adopt immersive virtual simulation technology. Immersive is the ultimate version of virtual simulation systems, allowing users to fully immerse themselves in a computer-generated world. Through head-mounted displays, users can observe scenes in three dimensions based on their position and direction. These systems can be enhanced through audio, tactile, and sensory interfaces. 2021 is referred to as the “Year of the Metaverse.” How can a ‘Metaverse’ system for university English be constructed to enable each student to take responsibility for their virtual identity and engage in university English learning activities within the “Metaverse” according to teachers' requirements and their own circumstances? This is also a question that can be further explored while constructing a university English intelligent adaptive system.

From the perspective of university English teaching models, it is recommended to adopt a blended online and offline teaching model. Currently, university English credits have been significantly reduced, and classroom instruction alone cannot achieve the teaching objectives of university English. Therefore, the intelligent adaptive learning system for university English can effectively compensate for the insufficient time in offline classroom instruction, enabling students to learn without spatial or temporal constraints and facilitating personalized learning.

However, university English education cannot completely detach from offline classroom instruction. The leading role of teachers must not be overlooked. While teachers should play a leading role in guiding, inspiring, and monitoring the teaching process, the proactive, positive, and creative nature of students as the main participants in the learning process must also be fully reflected.

III. B. Study Design

(1) Research sample

Two English teachers' lessons on “College English I” were selected as the research sample (Lesson 1 and Lesson 2). In Lesson 1, the teacher used the iFIAS English intelligent adaptive learning system designed in this paper for teaching, while in Lesson 2, the teacher used conventional teaching methods. Teachers' pedagogical philosophies and teaching habits may vary by region, so high-quality lessons from the same region can to some extent represent the teaching standards of that region and serve as the most direct model for local peers. By coding and quantitatively analyzing classroom teacher-student interaction behaviors in the same lesson, one can gain a deeper understanding of how high-quality teachers conduct classroom teacher-student interactions.

(2) Research Tools

To facilitate researchers in recording and classifying classroom teacher-student interaction language, Professor Fang Haiguang and his team developed the iFIAS coding program as an auxiliary research tool. iFIAS is divided into four modules and 14 dimensions [43]. The four modules are teacher language, student language, silence, and technology. Among the 14 dimensions, dimensions 1–7 pertain to teacher language, dimensions 8–10 pertain to student language, dimensions 11–12 pertain to silence, and dimensions 13–14 pertain to technology. The improved Flanders Interaction Analysis System is shown in Table 4.

Table 4: iFIAS

Category		Number	Behavior
Teacher language	Indirect influence	1	Teachers accept emotions
		2	Teachers praise or encourage
		3	Teachers adopt students' opinions
		4	Teacher questions (open questions, close questions)
	Direct influence	5	Teacher teaching
		6	Teacher indication
		7	Teachers criticize or maintain authority
Student language	-	8	Student passive response
	-	9	Student active speaking (active response, active question)
	-	10	Students and peer discussions
Silence	-	11	Not helping the chaos of the teaching
	-	12	helping the silence of the teaching
Skill	-	13	Teacher control technology
	-	14	Student control technology

Researchers simply need to enter the corresponding codes for classroom interaction behaviors into the coding program interface. Once completed, the system will automatically generate an Excel spreadsheet. The spreadsheet is then imported into the iFIAS analysis program, which produces the corresponding analysis results. The iFIAS coding program significantly reduces the workload for scholars, making the analysis process more efficient.

The iFIAS system designed by Professor Fang Haiguang and the coding assistance tools developed by his team were used to conduct quantitative analysis on selected high-quality lesson samples.

(3) Data Recording and Coding

iFIAS requires observers to record interactive behaviors every 3 seconds, following the standards outlined in Table 4. The iFIAS analysis program automatically generates a matrix analysis table in sequence. Using the iFIAS coding program to process the data, the frequencies and proportions corresponding to each code are obtained, as shown in Table 5.

Table 5: Statistics of course number frequency and proportion

Number	Behavior		Course 1		Course 2	
			Frequency	Proportion	Frequency	Proportion
1	Teachers accept emotions		0	0%	0	0%

2	Teachers praise or encourage		0	0%	11	1.39%
3	Teachers adopt students' opinions		32	3.9%	35	4.41%
4	Teacher questions	Open questions	28	3.42%	22	2.78%
		Close questions	32	3.9%	34	4.29%
5	Teacher teaching		267	32.56%	310	39.09%
6	Teacher indication		47	5.73%	51	6.43%
7	Teachers criticize or maintain authority		0	0%	0	0%
8	Student passive response		198	24.15%	60	7.57%
9	Student active speaking	Active response	36	4.39%	28	3.53%
		Active question	32	3.9%	19	2.4%
10	Students and peer discussions		18	2.2%	30	3.78%
11	Not helping the chaos of the teaching		0	0%	0	0%
12	helping the silence of the teaching		102	12.44%	115	14.5%
13	Teacher control technology		28	3.41%	78	9.84%
14	Student control technology		0	0%	0	0%
Total			820	100%	793	100%

(4) Dimensions and algorithms

The iFIAS system analyzes the data collected in the previous stage according to five dimensions (classroom interaction structure characteristics, teaching style characteristics, teacher-student emotional atmosphere, teacher-student question-and-answer characteristics, and dynamic curve characteristics), as shown in Table 6.

Table 6: iFIAS analysis dimension

Dimension	Sub-dimension
Class interaction structure characteristics	Teacher language ratio
	Student language ratio
	The proportion of teacher and student language
	Peer discussion ratio
	The proportion of silence good for teaching
	Technology usage ratio
Teaching style characteristics	Teacher indirect language and direct language ratio
	The positive influence of the teacher and the negative impact ratio
Emotional characteristics of teachers and students	The proportion of active integration region
	The proportion of negative integration region
	Positive and negative ratio
Teacher and student question and answer characteristics	The proportion of teacher question in teacher language
	The proportion of teacher open question in teacher question
	The proportion of teacher close question in teacher question
	The proportion of student active response in student speaking
	The proportion of student active question in student speaking
	Student active response and passive response ratio
Dynamic curve characteristics	The number of interaction lines between teachers and students

III. C. Research Results and Discussion

III. C. 1) Teacher-student speech behavior ratio in Lesson 1 and Lesson 2

Based on the statistical results in Table 5 of Section 3.2, the author calculated the ratios of teacher-student verbal behavior for Lesson 1 and Lesson 2. The research findings indicate that teacher-student interaction behaviors in the two classroom models share common characteristics while also exhibiting significant differences.

(1) Analysis of the common characteristics of teacher-student verbal behavior in Lesson 1 and Lesson 2

Some ratios of teacher-student verbal behavior in the two classroom models are very similar, such as: teacher verbal ratio (Codes 1-7), student verbal ratio (Codes 8-10), teacher direct influence ratio (Codes 1-4), and teacher indirect influence ratio (Codes 5-7), etc. Specific details are shown in Table 7.

According to the coding table of this study, teacher classroom speech behaviors include lecturing, giving instructions, criticizing, encouraging and praising students, adopting student opinions, and asking questions. The teacher speech ratios for Lesson Example 1 and Lesson Example 2 are 49.5% and 58.4%, respectively. Student verbal behaviors include passive responses, active responses, active questioning, and peer discussions. The student verbal ratios for Lesson 1 and Lesson 2 are 34.6% and 17.3%, respectively. In the overall classroom verbal interaction, the behaviors of teachers and students in Lesson 1 are balanced, with good teacher-student interaction. Teachers do not dominate the classroom discourse, and students have ample opportunities for classroom language practice, especially listening and speaking exercises.

The data also showed that the direct influence ratios of teachers in Lesson 1 and Lesson 2 were 38.3% and 45.5%, respectively, while the indirect influence ratios of teachers in Lesson 1 and Lesson 2 were 11.2% and 12.9%, respectively. In both classroom models, the direct influence ratio of teachers is greater than the indirect influence ratio, indicating that teachers play a dominant role in classroom interaction activities. In foreign language classroom teaching, the teacher's role should be that of a language environment designer or interactive teaching organizer. Their responsibility is to provide students with as many opportunities as possible for language practice. Therefore, this set of common data indicates that teachers in both Lesson 1 and Lesson 2 are striving to create an interactive classroom that encourages student participation.

Table 7: The common characteristics of language behavior of teacher and student

Language behavior ratio	Course 1/%	Course 2/%
Teacher language ratio	49.5%	58.4%
Student language ratio	34.6%	17.3%
Teacher direct influence ratio	38.3%	45.5%
Teacher indirect influence ratio	11.2%	12.9%

(2) Analysis of the distinctive features of teacher-student verbal behavior in Lesson Example 1 and Lesson Example 2

In the two classroom models, some ratios of teacher-student verbal behavior showed significant differences, such as the ratio of open-ended questions posed by teachers, the ratio of closed-ended questions posed by teachers, the ratio of active responses by students, the ratio of passive responses by students, and the ratio of classroom silence. The distinctive features of teacher-student verbal behavior are shown in Table 8.

In Lesson Example 1, the teacher not only posed a large number of open-ended questions but also encouraged students' comprehensible language output. This can be verified by the ratio of students' active responses. According to the coding table, students' active responses include freely expressing their own ideas and problem-solving approaches, stating the results of free discussions, role-playing, etc. The rates of active responses in Lesson Example 1 and Lesson Example 2 were 4.4% and 3.5%, respectively, while the rates of passive responses were 24.2% and 7.6%, respectively. These two sets of data also indicate that students in Lesson Example 1 not only produced comprehensible language but also demonstrated higher levels of mental activity.

Table 8: Differences in the language behavior of teacher and student

Language behavior ratio	Course 1	Course 2
Teacher open question ratio	46.7%	39.3%
Teacher close question ratio	53.3%	60.7%
Student active response ratio	4.4%	3.5%
Student passive response ratio	24.2%	7.6%
Class silence ratio	12.4%	14.5%

III. C. 2) Characteristics of Teacher and Student Speech Acts in Lesson Examples 1 and 2

To further investigate the characteristics of verbal behavior between teachers and students in the classroom, the author created a verbal behavior characteristic curve diagram. The horizontal axis of the diagram represents time in minutes, while the vertical axis represents the ratio of teacher or student behavior per minute. This diagram is used to describe how the ratio of teacher or student behavior changes over time. The comparison curves of teachers' speech characteristics between Lesson 1 and Lesson 2 are shown in Figure 4, while the comparison curves of students' speech characteristics between Lesson 1 and Lesson 2 are shown in Figure 5.

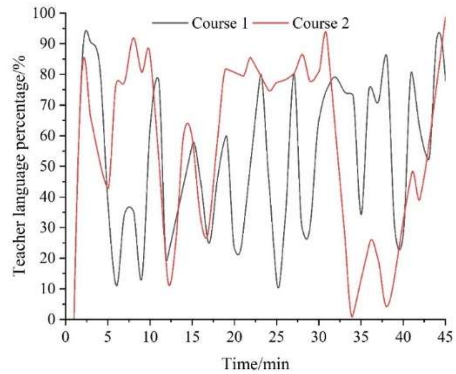

Figure 4: Teacher language characteristic curve

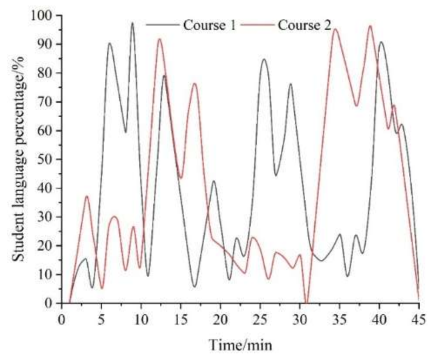

Figure 5: Student language characteristic curve

(1) Analysis of Teacher-Student Speech Curve Characteristics and Classroom Teaching Behavior in Lesson Example 2

Figure 4 shows that the teacher's speech behavior in Lesson Example 2 was concentrated in the first 35 minutes. Figure 5 shows that the peak of student speech behavior in Lesson Example 2 occurred after 31 minutes. The teacher's speech behavior was more frequent than that of the students in the first half of the lesson, highlighting the teaching characteristic of “input” promoting “output” in Lesson Example 2. Based on classroom observations, this study found that the teacher in Lesson 2 first used warm-up exercises to guide students' interest in the classroom topic. Therefore, the teacher's verbal activities were more frequent in the first half of the class, while students' responses were relatively passive. As the lesson progressed, the teacher organized peer discussions, resulting in a decrease in the teacher's verbal behavior and a gradual increase in students' verbal behavior.

(2) Analysis of the teacher-student speech curve characteristics and classroom teaching behavior in Lesson 1

Figure 4 shows that the teacher's speech behavior in Lesson 1 is distributed relatively evenly throughout the class. It enters a peak state from the first 2 minutes of the class, then appears at regular intervals, totaling 11 times until the end of the class. Figure 5 shows that the students' speech behavior in Lesson 1 reaches its first peak state in the first 5 minutes of the class, then appears at regular intervals, totaling 8 times. As shown in the figures, teacher and student verbal interactions in Lesson Example 1 were frequent and balanced throughout the lesson, with no instances of the teacher dominating the lesson or students controlling the classroom through their verbal behavior. In Lesson 1, teachers and students quickly entered a state of verbal interaction from the start of the class, which may be due to changes in students' learning methods. Since the topic background and main content of the class were already communicated to students through the learning platform before class, the diverse exercises organized by the teacher in class enabled students to respond quickly.

As shown in Figures 4 and 5, teacher-student language interaction activities in Lesson Example 1 were more frequent and closely integrated. In the Lesson Example 1 model, the students' learning process was inverted, with the primary purpose of the classroom being student language application and language output activities, leading to a large number of peer-to-peer and teacher-student interaction behaviors. These interaction behaviors are very important for language learning. During second language output, learners often rely on the feedback from listeners to correct their language forms, adjust and refine the semantics and grammar to facilitate smooth communication. Learners first focus on language features to establish hypotheses, which are then confirmed, corrected, or negated through feedback. This interactive process represents a higher-level processing of language analysis rather than mere language skill drills. Repeated and diverse language output combined with continuous feedback leads to increasingly accurate language use among second language learners. This paper presents an English intelligent adaptive learning system based on iFIAS, which provides authentic and positive activities and feedback for peer-to-peer and teacher-student interactions. This system helps students achieve language acquisition goals, far surpassing the practice of simple language skills, and better promotes language mastery.

IV. Optimization recommendations

Based on the above analysis, the following optimization recommendations are proposed to improve teacher-student interaction in the classroom, promote teacher professional development, and enhance the quality of teacher-student interaction.

(1) Optimize the classroom interaction environment to create a relaxed and interactive atmosphere

University English courses have their own unique characteristics, and active interaction between teachers and students in the classroom helps students master English knowledge and improve their communication skills. Teachers should strive to create a positive and free interactive environment, maintain a warm and harmonious teacher-student relationship, encourage students to think actively, ask questions boldly, and identify and pose challenging questions, thereby inspiring new ideas, sparking new perspectives, and initiating meaningful interactive activities. At the same time, teachers should actively embrace students' new perspectives, encourage students to speak up confidently and engage enthusiastically, and enhance students' sense of psychological safety.

(2) Optimizing classroom interaction models to enhance interaction efficiency

The interactive model in university English classrooms should gradually shift from teacher-student interaction to student-student interaction, transforming the traditional teacher-centered interaction model into a student-centered, teacher-assisted type. For example, in verbal interaction, the focus shifts from the teacher to the students, encouraging them to communicate with peers using acquired knowledge to enhance communication skills and reinforce learning. Teachers act as facilitators to assist students in resolving challenges. During the learning process of vocabulary and grammar knowledge, interactive teaching models such as classroom quizzes and word games can be adopted to guide students in spontaneously mastering the knowledge they have learned.

(3) Optimize classroom question-and-answer methods to stimulate student interaction Teachers can use information-based teaching methods to set up question-and-answer formats such as quick response, brainstorming, and classroom quizzes to stimulate students' enthusiasm for participating in answering questions.

(4) Optimize feedback methods to establish positive interactive relationships

After students respond, it is essential for teachers to provide positive feedback. Teachers should actively respond to students' answers to enhance their proactive participation. Additionally, for incorrect answers, feedback should be provided in a calm tone to help students recognize their mistakes and gain the courage and confidence to correct them. Teachers can also use a questioning tone to follow up on students' answers, guiding them to think deeply, stimulating their interactive initiative, and encouraging them to actively express their own views, thereby enhancing their classroom participation.

V. Conclusion

This paper proposes a deep knowledge tracking model (DKT-FA) based on feature embedding and attention mechanisms to track knowledge in English teaching and evaluates the performance of the DKT-FA model. A university English intelligent adaptive learning system was designed and developed to study the English classroom environment by analyzing teacher-student interactions.

The prediction accuracy of DKT-FA significantly outperforms other models, demonstrating superior performance. In Lesson 1 and Lesson 2, the teacher speech ratio was 49.5% and 58.4%, respectively, while the student speech ratio was 34.6% and 17.3%, respectively. The teacher direct influence ratio was 38.3% and 45.5%, respectively, and the teacher indirect influence ratio was 11.2% and 12.9%, respectively. The student active response rates were 4.4% and 3.5%, respectively, and the passive response rates were 24.2% and 7.6%, respectively. Lesson 1 demonstrated a more pronounced advantage. In Lesson 2, the teacher's instructional characteristics were characterized by “input” promoting “output,” with teacher speech behavior exceeding student speech behavior in the first half of the lesson. In Lesson 1, teacher speech behavior was more evenly distributed. Overall interaction between teachers and students was frequent, with more balanced interaction.

Funding

1. Research Project on Teaching Reform of Ordinary Undergraduate Colleges and Universities in Hunan Province - Xiangjiao Tong [2024] No.147, "Research on the Cultivation of Teaching Practice Ability of English Normal Students in Local Universities under the Background of Professional Accreditation" (Project No.: 202401001401).

2. Special Project on School-School Cooperation in the 14th Five-Year Plan of Chenzhou City Education Science for 2024 - Chenjiaokegui [2024] No.1, "Research on the Hybrid Model of English Teacher Training Skills Practice under the Background of Normal Major Accreditation" (Project Number: CJK24BXXHZ18).

References

[1] Uiboleht, K., Karm, M., & Postareff, L. (2018). The interplay between teachers' approaches to teaching, students' approaches to learning and learning outcomes: A qualitative multi-case study. Learning Environments Research, 21, 321-347.
[2] Faulconer, E. K. (2017). Increasing Student Interactions With Learning. Journal of College Science Teaching, 46(5), 32-38.
[3] Kamran, F., Kanwal, A., Afzal, A., & Rafiq, S. (2023). Impact of interactive teaching methods on students learning outcomes at university level. Journal of Positive School Psychology, 7(7), 89-105.
[4] Suryati, N. (2015). Classroom interaction strategies employed by English teachers at lower secondary schools. Teflin Journal, 26(2), 247.
[5] Li, J., & Xue, E. (2023). Dynamic interaction between student learning behaviour and learning environment: Meta-analysis of student engagement and its influencing factors. Behavioral Sciences, 13(1), 59.
[6] Nurpahmi, S. (2017). Teacher talk in classroom interaction. ETERNAL (English, Teaching, Learning, and Research Journal), 3(1), 34-43.
[7] Saifudin, S., Mispani, M., & Setiawan, D. (2024). The Teacher's Efforts in Improving Students' Interest in Learning through Interactive Learning Strategies. International Journal on Advanced Science, Education, and Religion, 7(2), 150-159.
[8] Tianjuan, Z. (2019, May). Methods of stimulating students' interest in English learning. In 2019 4th International Conference on Social Sciences and Economic Development (ICSSED 2019) (pp. 472-475). Atlantis Press.
[9] Putri, K. I., & Putri, H. P. (2021). The analysis of classroom interaction in English class using foreign language interaction. Modality Journal: International Journal of Linguistics and Literature, 1(2), 78-90.
[10] Shawaqfeh, A. T., Jameel, A. S., Al-adwan, L. A. Y., & Khasawneh, M. A. S. (2024). Interaction as a mechanism to enhance English language proficiency in the classroom. Journal of Language Teaching and Research, 15(1), 229-234.
[11] Siddig, B. E., & AlKhoudary, Y. A. (2018). Investigating Classroom Interaction: Teacher and Learner Participation. English Language Teaching, 11(12), 86-92.
[12] Kurniatillah, R. E., Hidayat, D. N., Husna, N., & Alek, A. (2022). Teacher-student interaction in English classroom setting. Journal of Applied Studies in Language, 6(1), 53-63.
[13] Sari, F. M. (2018). Patterns of teaching-learning interaction in the EFL classroom. Teknosastik, 16(2), 41-48.
[14] An, J., & Macaro, E. (2025). Exclusive use of the second language in classroom interaction in English medium instruction science classrooms: The beliefs of students and their monolingual teachers. Language Teaching Research, 29(2), 837-859.
[15] Xalilova, L., Turgunboeva, M., Shoxsanam, B., & Tojiev, X. (2021). Interactive methods in English classes. European Scholar Journal, 2(2), 48-50.
[16] Rido, A., & Sari, F. M. (2018). Characteristics of Classroom Interaction of English Language Teachers in Indonesia and Malaysia. International Journal of Language Education, 2(1), 40-50.
[17] Tasheva, N. (2024). THE ROLE OF INTERACTIVE METHODS IN TEACHING ENGLISH. Modern Science and Research, 3(1), 12-18.
[18] Azmat, M., & Ahmad, A. (2022). Lack of social interaction in online classes during COVID-19. Journal of Materials and Environmental Science, 13(2), 185-196.
[19] Snow, C. E. (2014). Understanding social interaction and language acquisition; sentences are not enough. In Interaction in human development (pp. 83-103). Psychology Press.
[20] Poulou, M. (2014). The effects on students' emotional and behavioural difficulties of teacher–student interactions, students' social skills and classroom context. British Educational Research Journal, 40(6), 986-1004.
[21] Solheim, K., Ertesvåg, S. K., & Dalhaug Berg, G. (2018). How teachers can improve their classroom interaction with students: New findings from teachers themselves. Journal of Educational Change, 19(4), 511-538.
[22] Bhattarai, J., Gnawali, L., Laudari, S., & Shrestha, S. (2021). Lack of participation in classroom interaction. Exploratory Action Research Stories of Nepalese EFL Teachers, 26.
[23] Peña-Ayala, A. (2013). Intelligent and Adaptive Educational-Learning Systems. eleed, 9(1).
[24] Koutsantonis, D., Koutsantonis, K., Bakas, N. P., Plevris, V., Langousis, A., & Chatzichristofis, S. A. (2022). Bibliometric literature review of adaptive learning systems. Sustainability, 14(19), 12684
[25] Khosravi, H., Sadiq, S., & Gasevic, D. (2020, February). Development and adoption of an adaptive learning system: Reflections and lessons learned. In Proceedings of the 51st ACM technical symposium on computer science education (pp. 58-64).
[26] Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. Computers and education: Artificial intelligence, 2, 100017.
[27] Lim, L., Lim, S. H., & Lim, W. Y. R. (2023). Efficacy of an adaptive learning system on course scores. Systems, 11(1), 31.
[28] Delgado, H. O. K., de Azevedo Fay, A., Sebastiany, M. J., & Silva, A. D. C. (2020). Artificial intelligence adaptive learning tools: the teaching of English in focus. BELT-Brazilian English Language Teaching Journal, 11(2), e38749-e38749.
[29] Ezzaim, A., Dahbi, A., Aqqal, A., & Haidine, A. (2024). AI-based learning style detection in adaptive learning systems: a systematic literature review. Journal of Computers in Education, 1-39.
[30] Kasinathan, V., Mustapha, A., & Medi, I. (2017, May). Adaptive learning system for higher learning. In 2017 8th international conference on information technology (ICIT) (pp. 960-970). Ieee.
[31] Ennouamani, S., & Mahani, Z. (2017, December). An overview of adaptive e-learning systems. In 2017 eighth international conference on intelligent computing and information systems (ICICIS) (pp. 342-347). IEEE.
[32] Mirari, K. (2022). The effectiveness of adaptive learning systems in personalized education. Journal of Education Review Provision, 2(3), 107-115.
[33] Rizwan, M. (2024). AI IN PERSONALIZED EDUCATION: ADAPTIVE LEARNING SYSTEMS. Computer Science Bulletin, 7(01), 43-50.
[34] Mei, J., Guo, Y., & Li, X. (2017). Adaptive Learning Mode of a Multimedia-based" English Literature" Learning System. International Journal of Emerging Technologies in Learning, 12(1).
[35] Bradac, V., & Walek, B. (2017). A comprehensive adaptive system for e-learning of foreign languages. Expert systems with applications, 90, 414-426.

[36] Hsieh, T. C., Wang, T. I., Su, C. Y., & Lee, M. C. (2012). A fuzzy logic-based personalized learning system for supporting adaptive English learning. Journal of Educational Technology & Society, 15(1), 273-288.
[37] Bourekkache, S., & Kazar, O. (2020). Mobile and adaptive learning application for English language learning. International Journal of Information and Communication Technology Education (IJICTE), 16(2), 36-46.
[38] Lawrance, J. C., Sambath, P., Shiny, C., Vazhangal, M., & Bala, B. K. (2024, March). Developing an AI-assisted multilingual adaptive learning system for personalized English language teaching. In 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 428-434). IEEE.
[39] Kumar, A. P., Fatma, G., Sarwar, S., & Punithaasree, K. S. (2025, January). Adaptive Learning Systems for English Language Education based on AI-Driven System. In 2025 International Conference on Intelligent Systems and Computational Networks (ICISCN) (pp. 1-5). IEEE.
[40] Lankun Guo,Jingyi Zhang,Guozhi Ma & Jianhua Dai. (2025). A deep knowledge tracing model based on cognitive assimilation and item response theory with better interpretability. Applied Soft Computing,180,113331-113331.
[41] Mousumi Sabat,Nachiket Kotwaliwale & Pramod Shelake. (2025). Non‐Invasive Prediction of Moisture Content of Potato Slices During Drying Using Wavelet Scattering Features and LSTM. Journal of Food Process Engineering,48(6),e70158-e70158.
[42] Zhou Yao,Mengting Yao,Chuang Wang,Ke Li,Junhao Guo,Yingjie Xiao... & Jianxiao Liu. (2025). GEFormer: a Genomic Prediction Method of Genotype-Environment Interaction in Maize by Integrating Gating Mechanism MLP and Linear Attention Mechanism. Molecular plant,18(3),527-549.
[43] Cai Su,Niu Xiaojie,Wen Yuxi & Li Jiangxu. (2023). Interaction analysis of teachers and students in inquiry class learning based on augmented reality by iFIAS and LSA. Interactive Learning Environments,31(9),5551-5567.