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Research on Knowledge Tracking in Foreign Language Teaching Based on Neural Network Computing

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Knowledge tracking offers new opportunities for integrating intelligent assistance in foreign language teaching, greatly promoting foreign language teaching in terms of research generally to accurate tracking of student progress, and suggestions. When teaching a foreign language, it is essential that teachers track students' knowledge acquisition scientifically and accurately. In order to establish and optimize the foreign language information-assisted teaching environment, this paper first proposes the integration of big data in foreign language teaching, and improves the mutual adaptation of the teaching environment. Next, it strengthens the construction of teaching informatization, then conducts an in-depth exploration of knowledge measurement in foreign language teaching and the tracking of students' knowledge level. Finally, the paper demonstrates that the proposed knowledge tracking model can improve students' overall learning outcomes. By means of effective, multi-dimensional and multi-index analysis methods, the paper explores the main problems that currently challenge the teaching of a foreign language. Through the data collection, knowledge point coding, testing and analysis in the process, the neural network computing knowledge tracking model is designed to indicate the students' recall of information, effectively track students' level of knowledge mastery, and optimize and improve teaching practices. The knowledge tracking study of 352 students shows that it is feasible to divide knowledge points according to 15 semantics, 46 phrases, 63 grammars, 95 structures and 126 logical relationships. Data preprocessing of knowledge tracking is necessary, as it determines the effectiveness and stability of knowledge tracking, and indicates that students' knowledge level and forgetting level follow certain rules. The reasoning ability of the model is improved after integrating knowledge tracking and forgetting information. The effective application of the knowledge tracking model can improve teachers' teaching efficacy and students' autonomous learning ability. The proposed knowledge tracking model and path for foreign language teaching is a new method that strengthens the driving force of informatization and provides a new means of improving and fostering foreign language learning.

Keywords: image dehazing; neural network computing; information management; knowledge tracking; foreign language teaching; model design

1. INTRODUCTION

In recent years, the use of information-based teaching aids for foreign language teaching has attracted increasing attention. From web technology, multimedia technology, virtual reality technology to 5G technology [1], various technologies have been integrated into foreign language teaching, with positive results in terms of experience and effect. However, the relevant researches on how to effectively track and guide students' learning situation are still in the exploratory stage. The teaching process is generally divided into four stages: knowledge preparation (formulation of training plan, construction of knowledge points and capacity matrix, writing of syllabus and preparation of teaching materials), imparting of information, knowledge assessment, capacity feedback and revision of training plan [2]. The first two stages of the teaching process focus on information transfer [3,4], and the latter two stages focus on knowledge measurement and tracking. This paper focuses on the latter two. In the teaching

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of a foreign language, a knowledge tracking model [5] needs to solve three problems: the first is the division of knowledge points, the second is the question bank data set designed according to knowledge points, and the last is the construction of appropriate knowledge tracking reasoning model. In the past, based on students' performance, subjective score, questionnaire responses and so on, it was impossible to quantify the input in this knowledge tracking model, although the model could reflect students' personalized and quantifiable indicators. Using a knowledge tracking model to track students' learning status can provide timely feedback regarding the level of mastery of knowledge points. Because of the decline of knowledge memory caused by students' memory declining, this paper proposes a knowledge tracking model integrating memory declining, which is verified as feasible on public and self-built data sets. By applying knowledge tracking to foreign language teaching, we can effectively improve students' knowledge level, analyze the influencing factors affecting students' knowledge mastery, and predict students' future learning outcomes.

2. APPROACH OF KNOWLEDGE TRACKING RESEARCH

2.1 Reform Measures of Knowledge Tracking in foreign Language Teaching

Using cloud resources available for foreign language teaching, Xiong et al. [6] proposed a simple and effective foreign cloud classroom learning method. The foreign cloud classroom measures the degree of students' participation in the classroom based on the student behavior model and amount of interaction. The research on foreign cloud classroom shows that students' participation in early foreign language teaching classroom activities is not high. In order to change this situation, research was conducted to obtain information about students' activities, and their relevant behavior, which can change over time in the classroom. The research results can be divided into three categories: students are not active, students engage in activities but this weakens over time, students are very active. The general trend is that the more active students are, the better their grades will be. Cloud classroom teaching also focuses on students' classroom behavior and learning activity model, and examines teachers' self-efficacy and teaching perception. Considering that the construction of cloud classroom resources is closely related to the mother tongue teaching environment and scenarios [7], more adequate preparations need to be made in the early stage, and specific appropriate strategies are also needed. In the research on foreign language teaching, the design and exploration of foreign corpus are very important elements. Foreign texts in a foreign corpus are a collection of original text materials, which are mostly from oral foreign language, novels, magazines, newspapers, academic articles, research institutions and examination evaluations. Due to the huge amount of data in the corpus, it is necessary to apply optimized intelligent computing methods to the corpus in order to ensure its maximum utility. In recent years, research has combined foreign corpora with actual foreign language teaching aiming to provide the best recommendation scheme. In order to construct the best foreign corpus, some researches [8] propose an excellent foreign corpus analysis scheme based on multiple data sources, since the construction of a corpus often ignores the importance of the data resources and dynamic fusion of algorithms, resulting in less effective application. Because a single data source is based on a single recommendation algorithm or simple fusion, a recursive neural network scheme is proposed based on a programmable, dynamic and adaptive recommendation algorithm [9], which can automatically classify sentences and texts derived from multiple foreign corpora. There may be significant differences between the meanings of translations and those of the original language. However, the language features of the translated foreign variants can be extracted by means of the multi-features statistical analysis method of the translated foreign corpus and the original corpus [10]. The collection and selection of foreign corpora play a very important role in the future of foreign language teaching work. Cross-cultural phenomena often occur in a corpus. Hence, theoretical support and clear explanatory principles are needed for the design of cross-cultural learning behaviors and activities. Heggernes [11] found that the data collected from novels are more extensive and more feasible, and are realistic. This research [1] focuses on student-centered learning and the strengthening of communication, and provides 36 empirical studies on foreign language teaching. The researcher believes that a corpus comprising different subject types is helpful for cross-cultural learning. Other different researches and optimized teaching methods also promote cross-cultural learning. Teachers' guidance is also very important in the process of foreign language learning. Taking ordinary universities and vocational colleges as an example, there are great differences in students' foreign language competence at the time of enrollment [12]. The main reason is that the students in vocational colleges do not have learning objectives and are confuse about what to learn, how to learn a foreign language and how to use a foreign language. Liu [13] studied methods for improving students' foreign language learning ability and participation in vocational colleges. Firstly, students need to have clear foreign language learning motivation by means of a foreign reading competition community; secondly Liu [13] proposes a social self-efficacy research model integrating extrinsic motivation and intrinsic motivation, which can predict students' willingness to participate in the competition in the future; finally, the researcher suggests teaching methods appropriate for the foreign language competition. The research shows that adopting the incentive model of foreign language competition teaching can significantly narrow the language gap between ordinary universities and vocational colleges. In the field of foreign language testing, the application of a cognitive diagnosis model is also a method worthy of exploration and research, as it plays an important role in giving personalized feedback reports in real time [14].

2.2 Knowledge Tracking Method

In China, foreign language teaching has advanced following the implementation of a series of educational reform measures. In recent years, the integration of students' learning state has further improved the level of foreign language teaching. Fernandez-Esquinas et al. [15] studied university-industry cooperation cases involving universities and 737 enterprises. The survey found that the university-industry chain has five dimensions: knowledge generation, human resources, intellectual property rights, educational activities, and educational facilities. Enterprises communicate with universities through various channels, from research project cooperation to content tracking involved in the teaching process. The researchers suggest that the effectiveness of university educational activities is positively correlated with the incentive policies for teachers and students. The terminal equipment and media forms used by students also have a certain impact on knowledge tracking. Schuler [16] conducted a comparative analysis of the various types of media that students used as teaching materials, such as text, pictures, and videos, concluding that different media forms will have an impact on the knowledge tracking of the target group, and the terminal equipment used for media display will facilitate knowledge tracking. In addition, the application of social media also plays an increasingly important role in knowledge tracking research. Bommel [17] tracked the teachers' knowledge structure through a Facebook group, and explored the composition of information, professional knowledge topics and teaching contents used to exchange relevant subject knowledge and language teaching. The research shows that the use of social media will improve students' ability to understand learning material. A further analysis of the factors affecting students' understanding of knowledge indicated that classroom teaching behavior plays a key role. The use of artificial intelligence technology to automatically record classroom teaching behavior can improve classroom teaching and assist with teaching and research activities [18]. Without an appropriate model, it is difficult to track the dynamics of the teaching process effectively. At present, the knowledge engineering system can generally support two knowledge processes: knowledge tracking and knowledge cataloging [19]. Gortzis has developed an n-tier system to support this process. In each stage, it adopts the personnel cooperation and prototype scalable knowledge engineering strategy, and uses the knowledge graph as the dynamic information structure. The knowledge engineering framework [20] has been proved to be effective in clinical management, as it can accurately predict the patients' risk level and reduce possible errors in the future. Meanwhile, the knowledge engineering framework is continuously being expanded and optimized through cooperation, which improves the performance of the whole system. In order to determine whether information resources are feasible and can be used effectively in the teaching process, according to the established structural equation model, Blau et al. [21] explored the influence mechanism operating between the dimensions of College Students' foreign learning information index system and the dimensions and constituent elements. With the support of appropriate models, combined with effective reasoning algorithms, the model can mine valuable information. Some studies have optimized the reasoning ability of the model through the sorting preference algorithm of main path analysis [22], allocated the model weight according to the role in knowledge distribution, further improved the knowledge reasoning ability after the combination of Louvain clustering algorithm and main path analysis, and visualized the overall knowledge structure through multiple paths, which has important implications for the exploration of this field. Zhang [23] proposed a Bayesian knowledge tracking model with three learning states. It extends the traditional two learning states, uses the tripartite decision evaluation function, divides a learning process into three equal parts, and corresponds to the three learning state models. Through qualitative and quantitative analysis, the study verified that the three learning states are more effective than the two tracking methods of learning state model. Sometimes the Bayesian knowledge tracking model needs to consider the gender of participating students, and the adaptability of different gender to the model is also different. Zhuhadar [24] analyzed the differences in the use of teaching resources in the intelligent teaching system according to the listening ability research. By means of extracted resource analysis and data monitoring, participants of different genders show the significant differences in Bayesian knowledge tracking and learning curve analysis model. The existing knowledge tracking model has gradually achieved results in predicting performance, determining the mastery level according to students' learning outcomes. However, in the knowledge tracking model, it is difficult to simulate students' memory about the learning process, especially given the short-term memory and long-term memory in the human memory mechanism [25]. However, by embedding a hierarchical memory network, it can better adapt to the human memory mechanism in knowledge tracking. The hierarchical memory in the hierarchical memory network is achieved by an external memory matrix and segmentation aging mechanism, and the short-term memory is simulated through the working storage matrix. The segmentation aging mechanism simulates long-term memory, and the model integrates the memory mechanism, which has important reference significance. The integration of memory into a knowledge tracking model can significantly improve the prediction accuracy, although students' individual learning characteristics cannot be ignored. Due to the differences in students' personal learning habits and knowledge levels, students' knowledge composition and previous learning status and other potential variables have a direct impact on the model. Through in-depth knowledge tracking, students' individual learning variables can be better used [26]. Combined with learning content and long-term and short-term memory network, it can accurately predict students' learning state. Students' learning state is potential and time-variant, so it is always difficult for a knowledge tracking model to track students' learning state in the long term. In the early stage, statistics were manually obtained by extracting students' homework and students' temporary examination ability, which required a great deal of time and effort. At present, the deep learning model can better solve this problem, but it is difficult to understand the parameters of the model, which makes the relevant applications slow. Su [27] further improved the performance of the model by proposing a new framework of deep multidimensional project response theory called 'time and concept enhancement'. The model contains two enhancement components which strengthens its prediction ability and enables the model parameters to understand easily.

2.3 Knowledge Tracking Design and Impact Analysis

The design of a knowledge tracking system includes four main processes: problem analysis, data collection, model design and tracking prediction. Knowledge tracking analyzes the server statistical logs related to students' learning and the statistical data of learning behavior published by third-party data sources, and constructs a knowledge tracking model for students' behavior data. It then obtains valuable, multi-dimensional and multi-index real-time prediction information and, finally, fan accurate feedback knowledge tracking system is created. Nowadays, educators believe that it is difficult to track effectively the current state of students' learning, and their level of knowledge mastery [28]. Although the relevant educational administration departments have saved students' daily learning data, the use of these data is still a problem. In order to solve these problems, we need to have an in-depth understanding of some key points related to student learning, such as the overall knowledge level, the number of careless errors, the average accuracy, the total number of learning login times, students' emotional/psychological state, the degree to which they are being affected by the entertainment game, cognitive skills related to the problem, the average length of time students spend on answering questions, students' self-confidence, and focus on the total length of knowledge tracking, the changes in teachers' guidance methods and their impact on students' skill improvement, and the possible influencing factors. The following two research questions play an important guiding role in this paper: Question 1: What effect does knowledge tracking have on teachers' teaching and students' skills improvement? Question 2: What factors will have an important impact on effective knowledge tracking?

3. METHOD

3.1 Participants

The data for this study were collected from 21 school teachers (14 males and 7 females) and 352 students (183 male and 169 female). From September 2018 to December 2021, all participants participated in knowledge tracking questions in at least 4 of the 7 semesters. The teachers have an average of 15 years of teaching experience, and students involved are taking one of four majors: public English, business English, tourism English and exhibition English. Teachers design the question bank before the beginning of the semester, and students can improve their skills by answering questions, judging, giving feedback, accepting teachers' feedback and guidance, answering questions again, and statistical analysis of teachers during the learning period. Participation was voluntary, confidentiality was assured, and the data was used for research purposes only.

3.2 Problem Analysis

During foreign language teaching and learning, a huge amount of data is generated by smart phones, iPads, computers, and other multimedia tools. These data pertain to students' learning and browsing, and some data record the students' participation (e.g. answering questions). A summary of the data yields five main attributes: user, knowledge, question, question answer and answer result. The difficulty of the questions can be determined by the students' answers, and the level of students' knowledge mastery can be analyzed. However, at present, foreign language teaching is still faced with the problem that students' future answers cannot be predicted from the past historical answers. In addition, information cannot be obtained regarding the decline of students' knowledge over time. To ensure that students master foreign language knowledge, attention should be paid not only to the construction of teaching resources, but also to the mining of students' potential rules of language learning knowledge. Also, the answer data should be analyzed. Using model calculation, effective answer data features are extracted to provide personalized professional guidance for students, and further promote the utilization of intelligent assistance in foreign language teaching.

3.3 Data Collection

The experimental data pertaining to foreign language teaching were collected from a self-built-knowledge-dataset, Mutual dialogue dataset [29], Microsoft machine reading comprehension dataset MS MARCO [30], Encarta data set, ASSISTments dataset [31] and KDD Cup dataset [32]. The self-built-knowledge-dataset is the student answer dataset which is based on a skills test, and which is also collected from the students' answer data over seven semesters, focusing on students' basic skill tests, such as listening, grammar, reading, cloze, etc. These skills are covered by 126 knowledge points. Each question provides only logically correct answers, usually evaluates only one skill, and covers several knowledge points. Some of the test questions included several irrelevant items to detect whether students have strong discrimination ability, which provides a more reasonable basis for achieving knowledge tracking in the self-built-knowledge-dataset. The mutual listening data set was based on retrieval dialogue reasoning, which was modified from the Chinese English listening test data. All the selected listening data were context related, and only one listening question was logically correct. In some cases, some of the irrelevant options were also apparently reasonable, but there was only one truly appropriate option. The reading comprehension data were derived from the Microsoft machine reading comprehension data set known as MS MARCO, which is a dataset for reading comprehension and large-scale question and answer tests. In MS MARCO, all questions are extracted from real anonymous user queries. The answers in the dataset came from the context, and were

Table 1 Data structure and meaning of knowledge tracking.

Hidden Variable	Observed Variable	Test Questions Status	Pursuit Tracking
Forgetting	Users	Answer performances	Circular memory
Skills	Knowledge points	Knowledge coverage	Reasoning abilities
Knowledge state	Questions	Accuracy	Knowledge transfer
Question types	Question answers	Missing values	Generalization ability
Practice frequency	Answer results	Feedback	Mastery

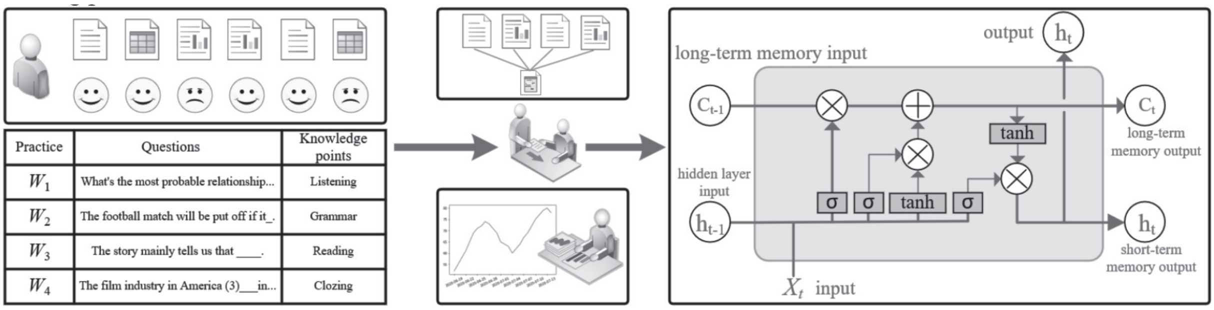

Figure 1 The data collection and research process of knowledge tracking.

extracted from documents found through search engines; the real answers to the reading comprehension questions were artificially generated. The Encarta question-and-answer dataset contains 1400 daily questions and a set of manual annotations that identify text fragments coming from fully- or partially-answered questions in Encarta. These annotations specify information about the exact match: for example, whether the language forms of questions and answers are similar. The annotation data is divided in two different ways to promote the training of different algorithm teaching models. ASSISTments is an association dataset about online tutoring teaching skills system, which was first built in 2004. Students participating in ASSISTments will get a new question after answering correctly, and if the answer is wrong, students are given a mini tutoring course. The common datasets are: ASSISTments 2009–201, ASSISTments 2012–2013 and ASSISTments 2014–2015. These data sets remove duplicate and multi-skill duplicate records. KDD Cup comes from Carnegie's cognitive counseling dataset. In this data set, problems are associated with multiple skills, and sometimes a subset of multiple skills can be regarded as a new skill. These constitute the largest open available knowledge tracking dataset. The data structure and meaning of knowledge tracking is shown in Table 1.

3.4 Procedures

The research was divided into three stages: the first stage involved the collection of the editing of test questions and the data of students' practice answers. The test questions covered the knowledge points of different types of questions such as listening, grammar, reading and cloze test. The different types of exercises consisted of multiple groups of test questions. The difficulty of each group of exercises was adjusted according to the students' situation after answering the questions, so that the difficulty finally tended to be moderate. In order to facilitate the tracking of students' knowledge acquisition, the knowledge was classified according to specific knowledge points; meanwhile, many test questions were formulated. The second stage involved the analysis of the test questions. They were each given a 'difficulty' score according to the average time taken to answer them, and the accuracy of students' answers to each question. The results indicated the overall level of students' knowledge. In the third stage, through a neural network model, the students' knowledge tracking path and forgetting curve is created based on students' learning outcomes in the past, present and future. Finally, gaps in students' knowledge are identified, and an effective learning path is established.

The left part of Figure 1 shows the students' answers according to the knowledge points. The data show the students' level of mastery of the relevant knowledge content. The data in the middle part shows the relevant knowledge concepts and statistical understanding obtained through a round of practice. These data can also indicate the students' learning dynamics and forgetting curve between different types of exercises. The right part of Figure 1 shows the students' answers and the related information of students' learning behavior extracted by the neural network model. After repeated training, the conclusion deduced by the model becomes more and more accurate. The structure of the collected data contains more auxiliary information, such as the subject information ID, homework ID, topic ID, user ID, knowledge point ID, teacher ID, student ID, etc. The knowledge tracking data tuple includes the names of knowledge point, answer duration, answers, answer types, answer times, test question types, terminal tool types, etc.

3.5 Teaching Design

Teaching design consists of four parts: constructing the exercises that students participate in, and then numbering the knowledge points according to the basic composition of the knowledge points in the course content; designing the forms

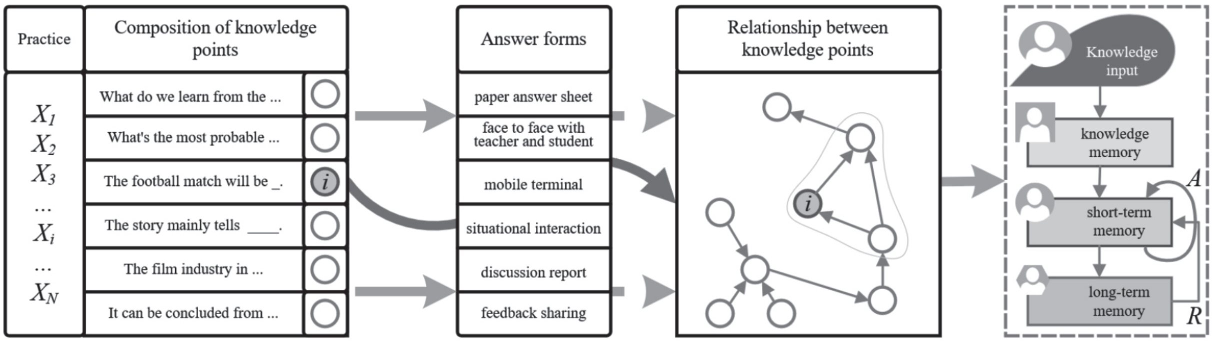

Figure 2 The Teaching Design of Knowledge Tracking.

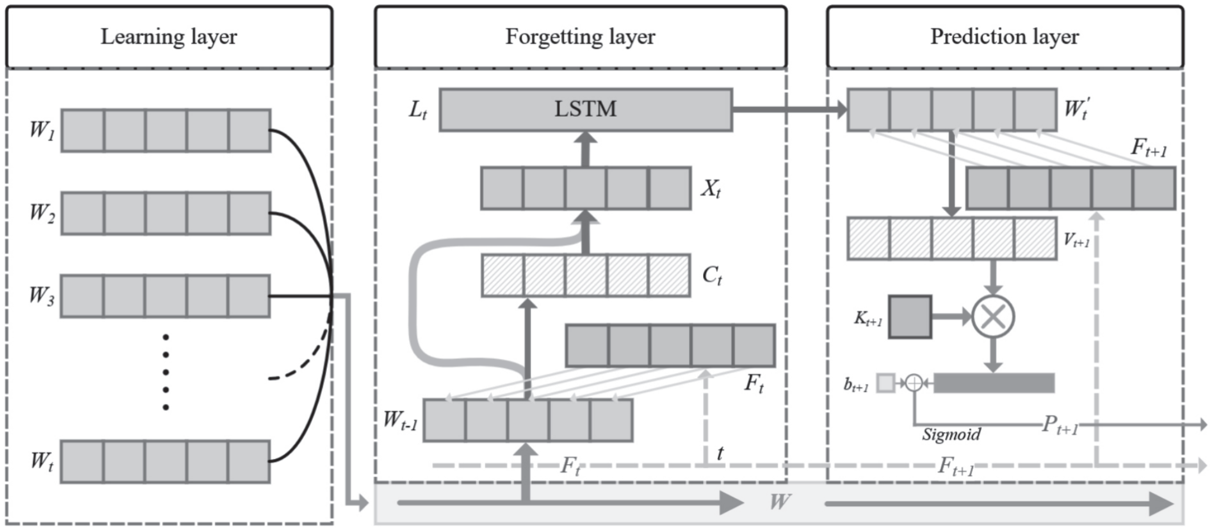

Figure 3 Knowledge tracking model.

that the students' answers will take, such as: paper answer card, face-to-face between teachers and students, mobile terminal, situational interaction, discussion report and feedback sharing; determining the relationship between knowledge points; consolidate students' mastery of knowledge points. The design of knowledge tracking teaching is shown in Figure 2.

A in the right-most column in Figure 2 represents the repeated memory of self-cyclic iteration of short-term memory, and R represents the recovery of long-term memory to short-term memory. According to the order of complexity from low to high, this teaching design method gradually advances from the design of knowledge point test practice to the knowledge assessment of various answer forms, to explore the correlation between knowledge points, innovate the traditional teaching method from memory enhancement, and express the static knowledge as a dynamically traceable process.

3.6 Model Design

In this paper, the knowledge tracking model is divided into three layers: learning layer, forgetting layer and prediction layer, as shown in Figure 3. In the learning layer, during students' interactive practice, the students' Practice Homework records are taken as the input vector of the system. W represents the data set of Practice Homework, W=$\{W_1,W_2,W_3,...,W_t,...\}$. Each time, the students' Practice Homework record will be marked as W_t =$\{U_t,Q_t,...,A_t,S_t\}$,t is the time of observation variable, U_t is the quantized value of student U at t time, Q_t is the quantized value of question Q at t time, A_t is the answer result of student, S_t value is 0 or 1, correct answer S_t =1, otherwise it is 0. All the information is encoded with unique heat coding as the input feature, but TF-IDF (Term Frequency-Inverse Document Frequency) coding [33] is not used because the research objects in this paper are students' answers and learning behaviors, the research objects are relatively stable, and the feature space is within the controllable range.

In the forgetting layer, F_t is the weight of the influencing factors of students' learning knowledge at t time, C_t is the vector combining the students' practice results at t-1 time and the influencing factors at t time in the learning layer, and C_t is fused with the previous students' practice results to obtain the input vector X_t of the forgetting layer LSTM [34]. In the prediction layer, the output of LSTM is the input $W_t{}'$, $W_t{}'$ obtains vector V_{t+1} after being acted by F_{t+1} at t+1 time, then combines with weight vector K_{t+1} and offset b_{t+1}, and outputs prediction result P_{t+1} through Sigmoid activation function.

In the traditional student knowledge tracking model [35], the forgetting of knowledge during students' learning process is not considered. Therefore, in the design of the proposed

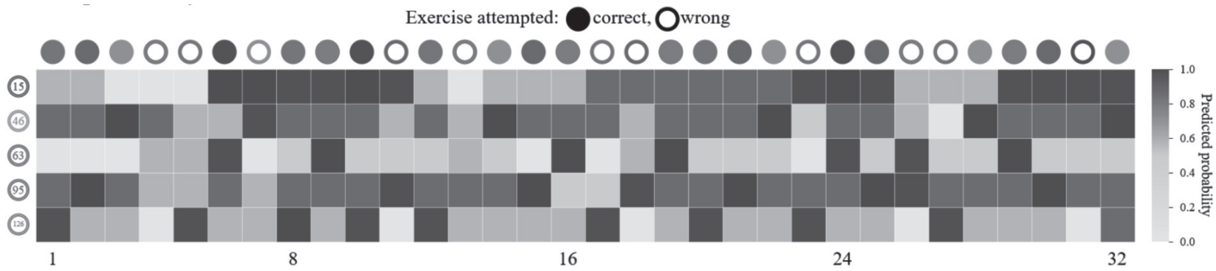

Figure 4 Visualization of students' mastery level of knowledge points.

Table 2 The description of observation on four levels.

Point of view	Basic knowledge level	Student emotion	Teacher guidance	Answer dynamics
Observation points	Grades of admission and prerequisite courses	Boring, focused, confused, depressed	Numbers of instructions and questions	Interval of continuous answer
Main purpose	Master the benchmark level of students	Master the current status of students	Numbers of teacher participation	Master students' memory ability
Impact	Affect the initial answer effect	Affect the current answer accuracy	Affect students' enthusiasm to answer questions	Affect knowledge retention

model, the influence of students' different learning behaviors on memory is fully considered. That is, the information on students' learning behavior and long-term and short-term memory network are integrated to enhance the knowledge-tracking capability of the model.

The forgetting information [36–37] is extracted from the students' answers, and applying it to English teaching assistance systems can significantly improve the level of intelligence [38]. It is judged according to the time, correctness, and time taken to answer the same question. The forgetting speed is inversely proportional to the interval, and the forgetting speed is quantified into 10 grades. The knowledge tracking model proposed in this paper can be used to predict students' mastery of relevant knowledge points and determine the factors that have a positive impact on students' learning.

4. EXPERIMENT AND RESULT ANALYSIS

4.1 The Impact of Knowledge Preprocessing and Reasoning

The mastery of knowledge points often permeates many different exercises. One exercise covers many examination questions pertaining to knowledge points. Students must master several knowledge points in one stage of learning. Taking a learning task as an example, the knowledge points that need to be mastered are: semantics, parts of speech, phrases, tense, sentence structure, sentence logic, text structure, etc. The observation sequence of a student's answer to a learning task is $W_t = \{U_t, Q_t, ..., A_t, S_t\}$. Figure 4 below shows the visual effect of knowledge tracking after this student answers on five knowledge points: 15 semantics, 46 phrases, 63 grammatical points, 95 structures and 126 logical relationships. This student attempted a total of 32 questions (horizontal axis), and in the deep knowledge tracking, each question is associated with a knowledge point. The 32 questions covered a total of 5 knowledge points. In the double circle on the left, the purple represents the knowledge point of "15 semantics", the green represents the knowledge point of "46 phrases", etc. The students' actual answers are shown in the circle at the top of the figure. The color of the circle indicates the knowledge point captured by this question. The filled circle indicates the correct answer and the hollow circle indicates the wrong answer. The blue orange grid in the middle of the figure indicates the prediction results of the model, and the change from orange to blue indicates that the probability of correct answers is increasing. Specifically, the student starts to answer three orange, blue and green questions correctly (check the "logical relations, structures and phrases" of knowledge points), then the model prediction accuracy of the first three columns of the knowledge points grid is blue (the probability of correct answer is high), while the other uninvestigated knowledge points are orange (the probability of correct answer is low), and the fourth and fifth questions are all wrong. The student's knowledge of logical relationships and grammar predicts that the probability of correct answers will decrease.

The preprocessing of knowledge tracking data involves two steps. First, it is necessary to delete records with missing values. For example, some students log in without answering questions. Secondly, students have different knowledge levels when answering questions during different semesters, resulting in inconsistent results, which will have an impact on the effect and stability of knowledge tracking.

4.2 The Effects of Different Observation Methods

The analysis of students' answer data involves four elements: basic knowledge level, students' emotion, teachers' participation and guidance, and answer dynamics. The

Table 3 The impact of changes in student answer data.

	Ideal times	Actual times	Impact classification
Basic knowledge level	7	4	Individual impact, short-term impact
Student emotion	21	6	Individual impact, short-term impact
Teacher guidance	42	15	Overall impact, long-term impact
Answer trends	84	38	Overall impact

Table 4 Proportion of respondents by category (five students have missing value in 352).

		Never answer questions	Answer questions correctly at least one	Answer questions correctly three consecutive times
Basic knowledge level	H	0% (0)	20.17% (71)	3.41% (12)
	M	0.57% (2)	45.74% (161)	1.42% (5)
	L	0.85% (3)	27.27% (96)	0.57% (2)
Student emotion	H	0.28% (1)	56.25% (198)	4.55% (16)
	L	1.14% (4)	36.93% (130)	0.85% (3)
Teacher guidance	H	0% (0)	91.19% (321)	5.11% (18)
	L	1.42% (5)	1.99% (7)	0.28% (1)

effects of different observation methods are given in Table 2 above. Generally, teachers' participation in guidance and answering dynamics have a greater impact on students' skill improvement. Students' emotions have fluctuating effects on students' skill improvement in the short term, but will not have much impact in the long term. However, the level of basic knowledge has a greater impact at the beginning of the semester and will not have a decisive impact in the following semesters (as shown in Table 3).

4.2.1 Knowledge Renewal Level

Give the above data and through the analysis of students' answer data, the interval between students' wrong answers and forgetting is closely related to the mastery of knowledge points. The reasoning model proposed in this paper can accurately indicate students' mastery of knowledge points and effectively remind students how long to consolidate the knowledge points.

The sorted knowledge points and student answer dataset are divided into two parts: training set and test set; the training set accounts for 80% of the dataset and the test set accounts for 20%. After the input model of the training set is trained repeatedly, a set of model super-parameters which can be used for subsequent reasoning are obtained. The reasoning model can predict students' answer performance and give a forgetting warning.

The mastery level L of a certain knowledge point of students can follow the formula: $L(k)$ = (1-μ)($P_k S_k$)/(?P_k) for calculation. In the formula, k represents a certain knowledge point, P_k represents the score of each question for knowledge point k, S_k represents the correct answer of question P_k for knowledge point k, and S_k value only takes 0 and 1 (indicating the wrong and correct answer), represents the inner product operation of vector, μ is a student's forgetting factor for knowledge point k, μ value takes between 0 and 1, the larger of μ value, the more the knowledge points are forgotten, and the lower the mastery level is, otherwise the higher the mastery level is, $\mu = 1 - \Sigma(r_i/2^i)$, I is the number of times to answer the question, r_i is the correct rate, and never answer the question $\mu = 1$. When answering questions correctly for 3 consecutive times $\mu = 0$. The percentages of respondents are shown in Table 4 below.

4.2.2 Predicting Knowledge Level

In the experiment, five evaluation indexes are used to calculate and predict the results, namely AUC, Recall, Precision, F1 and Acc. Precision =TP/(TP+FP). AUC refers to the Area Under Curve, which refers to the area under the ROC (Receiver Operating Characteristic) curve surrounded by the coordinate axis. Recall is called recall rate which is a measure of coverage. It measures the number of positive cases. In the Recall=TP/(TP+FN), TP (True Positive) refers to the number of positive classes predicted as positive classes, and FN (False Negative) refers to the number of positive classes predicted as negative classes. It often refers to missing reports. It can be seen that the recall rate is the same as the sensitivity.

Precision represents the proportion of real positive examples in the examples divided into positive examples. In the Precision =TP/(TP+FP), FP (False Positive) refers to the false alarm of predicting the number of negative classes as positive classes. F1 score is an index used to measure the accuracy of classification model in statistics, which considers the accuracy rate and recall rate of classification model at the same time. F1 score can be regarded as a harmonic average of model accuracy rate and recall rate, whose maximum value is 1 and the minimum value is 0, and F1=2 Recall Precision/(Recall + Precision). The optimization objectives of AUC are TP and (1-FP). Because the number of topics covered by various foreign language knowledge points is not uniform and the datasets are quite different, it is difficult to show the model has good adaptability by using only one evaluation index. Acc is the accuracy rate, which refers to the percentage of all correct predictions (positive and negative) in the total, and Acc= (TP +TN) / (TP + TN +FP+FN).

The data in Table 5 above shows that the knowledge tracking model is relatively stable through reasoning students' knowledge level, and the knowledge tracking model has a good prediction accuracy for students' future performance.

Table 5 The prediction evaluation index results of students' knowledge level based on knowledge tracking model.

Dataset	Precision	Recall	F1	ACC	AUC
Mutual	58.27	62.69	60.39	62.10	62.14
MS MARCO	65.36	68.30	66.80	66.80	66.83
Encarta	80.05	79.37	79.71	79.30	79.29
ASSISTments2015	74.07	75.39	74.72	75.02	75.03
KDDCup2010	70.06	69.54	69.80	69.30	69.29
Our dataset	84.71	79.56	82.05	82.10	82.18

Table 6 Comparison of knowledge tracking models before and after forgetting information integration.

KT	AUC	Recall	Precision	F1
Knowledge tracking model (without integration)	82.18	79.56	84.71	82.05
Knowledge tracking model (with integration)	88.17	89.51	85.29	87.35

Moreover, results indicate that the knowledge tracking model can quite accurately capture students' knowledge level. The integration of forgetting information into the knowledge tracking model can indicate the students' knowledge mastery and possible knowledge gaps in time, and help students further improve their foreign language learning ability by means of an effective learning path provided by the knowledge tracking model. The higher the AUC value, the greater is the accuracy of the model. The Recall is higher than before, which indicates that the increasing in the proportion of positive cases will be correctly judged. Precision and Recall affect each other. Ideally, both are expected to be high. However, in practice, Precision is high while Recall will be low; or Recall is low while Precision will be high.

4.2.3 Knowledge Forgetting Level

The experiment is divided into two groups datasets: the group with forgotten information and the group without forgotten information. By analyzing the result of forgotten information having different effects on the system, which is the extended research on the knowledge tracking model, the system can continuously optimize the adaptability of the model and further improve the prediction accuracy. Table 6 below shows the comparative effects of forgotten information before and after integration.

In Table 6, the results of AUC, Recall, Precision and F1 show that the reasoning performance of the knowledge tracking model after forgetting information has been integrated with it is better than that of the previous knowledge tracking model. This indicates that forgetting information plays a positive role in improving students' future learning performance and tracking their learning path. The main reason is that students' forgetting is inevitable in the learning process, but the decline of forgetting is closely related to the time-span and the frequency of revision. When the forgetting information is integrated into the knowledge tracking model, the reasoning ability of the model is significantly enhanced, which is also consistent with the real learning state, and the inferred students' knowledge level is also in line with the actual situation.

4.2.4 Individual Practice Level in Classroom

With the application of College English knowledge tracking teaching model, students' knowledge level has been continuously improving. When applying the knowledge tracking model to the teaching of College English, teachers implement six steps: the division and arrangement of knowledge points, the design of teaching plans, the design and compilation of test questions, the test and analysis of students' answers, the feedback of knowledge tracking model, and the optimization of teaching plans. This method is designed to improve pedagogy, cater for the individual learning needs of students, address gaps in students' knowledge at various points, and strengthen the students' ability to apply their knowledge when problem-solving.

Students' individual behaviors in the classroom can indicate their level of knowledge. Traditional teaching methods usually allow students to study independently with relatively less time. Teachers impart a great deal of information to students in the classroom, but pay less attention to the application of acquired knowledge. Through the effective application of the knowledge tracking model, starting from the perspective of practical problems in the process of students' knowledge acquisition, teachers should reform the teaching model by combining with knowledge points, situational cases, and practice in class, encourage students to practice their English skills in real-life situations, and attempt to improve students' desire and ability to learn independently.

4.2.5 The Influence of Structured Answers on Knowledge Tracking

At the reasoning and analysis stage, students' practice records are selected from the dataset for the purpose of prediction. The thermodynamic diagram of prediction probability statistics is visualized as shown in Figure 5. The vertical axis represents the extracted four knowledge points, which are: 48-word meanings, 63 grammatical tenses, 95 sentence structures and 126 sentence logics. The horizontal axis represents the students' answers to 24 questions. On the horizontal axis, (126,1) indicates that the logical answer to knowledge point 126 sentence logic is correct, while (63,0) indicates that the grammatical tense answer to knowledge

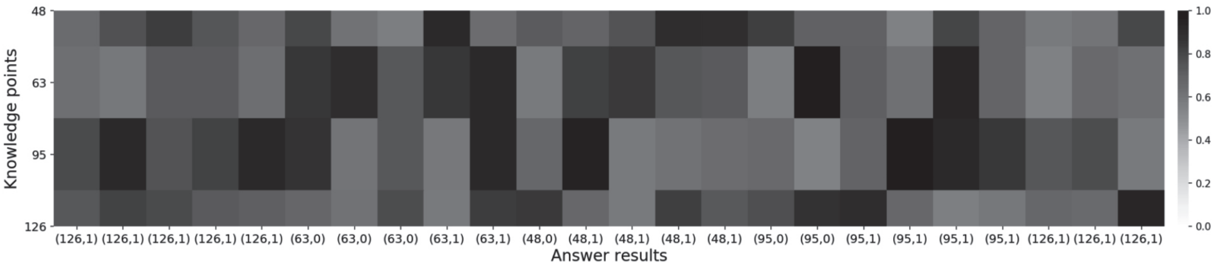

Figure 5 The results of knowledge point reasoning analysis.

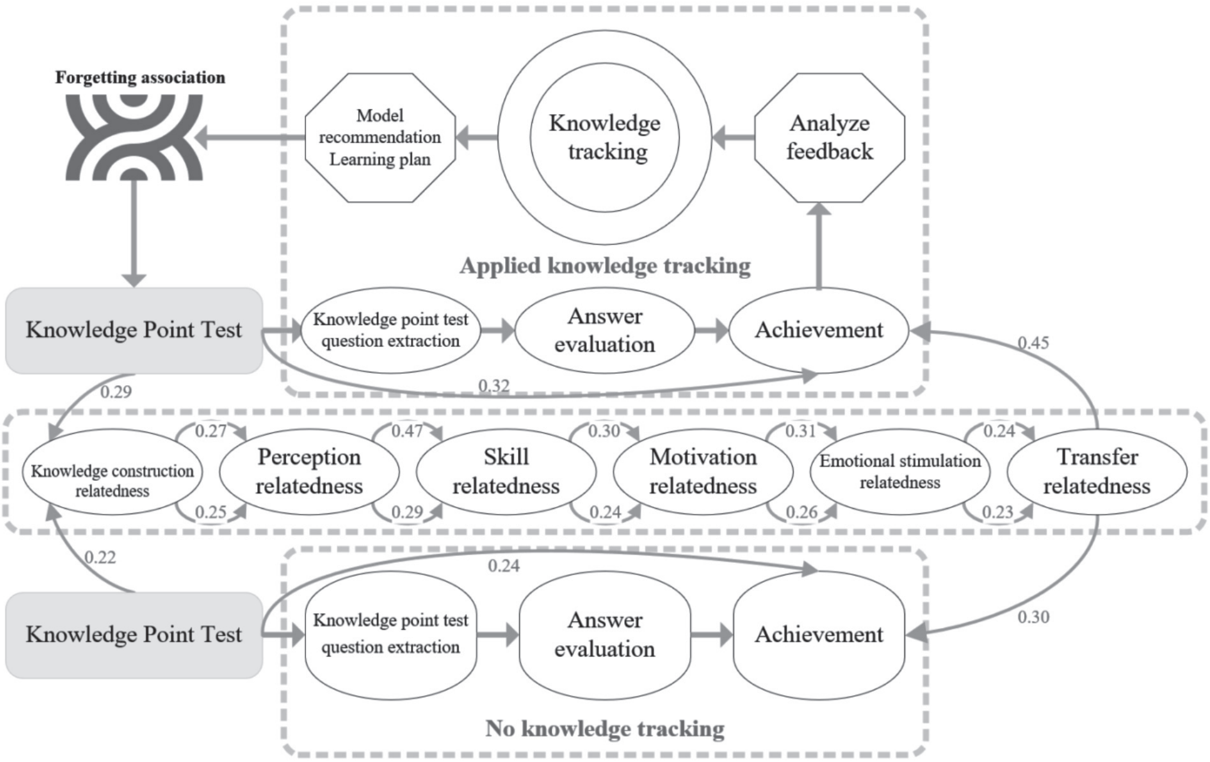

Figure 6 Adopting knowledge tracing reasoning model is beneficial to teaching assistance.

point 63 is wrong. The color depth of the square block indicates the probability of an answer being correct.

By extracting students' answers at specific knowledge points, the prediction of students' mastery of knowledge level based on the model is in line with teachers' general judgment, and can be adapted to long interval or non-relevant knowledge points. The change of the prediction of the accuracy of answers in a knowledge point reflects the dynamic change of students' mastery of knowledge. Through the data reasoning and analysis capability of the model, students' knowledge can be tracked effectively, and subsequent action can be taken to address any knowledge gaps.

4.3 Reasoning Analysis of the Knowledge Tracking Model

In order to evaluate the effectiveness of the knowledge tracking model, the evaluation of the reasoning model adopts two criteria,: (i) the coefficient of determination (R2) in the dependent variables, where R2 values 0–0.10, 0.11–0.30, 0.30–0.50, and $>$ 0.50 are indicative of weak, modest, moderate, and strong; (ii) the model's reasoning analysis, in which the model is tested based on a verification sample and its reasoning power assessed, the variables involved are: knowledge construction relatedness, perception relatedness, skill relatedness, motivation relatedness, emotional stimulation relatedness, transfer relatedness. The R2 value of the result variable is between 0.24 and 0.47 (applied knowledge tracking), indicating a moderate to strong effect, as shown in Figure 6. Specifically, the model has a strong ability to predict skill correlation (explaining about 47% variance), and then emotional stimulation relatedness (31%) and transfer relatedness (24%).

5. CONCLUSIONS

of the focus of this paper is a knowledge tracking model used in foreign language teaching. By considering the memory and forgetting information, the proposed model is more stable and more consistent with the actual situation, and better able to accurately determine the level of knowledge consolidation. The research path of the knowledge tracking model not only considers individual students' learning needs, but also considers teachers' needs for the subsequent examination of students' knowledge acquisition. However, the knowledge tracking model proposed in this paper has several shortcomings which need to be addressed in future work. For instance, the coding of input data needs to be improved as does the performance of the model. There is a need to obtain more information regarding optimized memory and forgetting of students with different personalities, and how to expand other learning characteristics, considering the issue of forgetting. This model has an impact on both teacher and students.

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