Application of Exercise-Correlated Knowledge Proficiency Tracing Model based on Multiple Learning Objectives in English Teaching Curriculum Resources

https://doi.org/10.3991/ijet.v17i24.35417

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Abstract—The advanced invention of information technology overcomes the limitations of traditional teaching methods. The English-oriented online teaching system not only has rich course resources, but also provides technical support for students' personalized learning. Therefore, using big data mining techniques may help to analyze students deeply and develop personalized study plans and content. Aiming at the deficiencies of online English teaching platform in the task of knowledge level diagnosis, an Exercise-correlated Knowledge Proficiency Tracing (EKPT) model that integrates multi-objective learning factors is proposed. The learning model maps students and practice information into meaningful knowledge space through practice and knowledge-related information, and quantifies students' knowledge learning process through forgetting curve theory and learning curve theory. The experimental test results show that the EKPT model has the best performance in knowledge ability prediction and learning performance prediction. The mean absolute error (MAE) values of the EKPT model in the English1 dataset, English2 dataset, written auxiliary dataset and adaptive dataset are 0.32, 0.25, 0.39 and 0.34, respectively, with the smallest error. Therefore, the proposed EKPT model meets the requirements of English online learning. The research content has important reference value for the construction of online English teaching platform.

Keywords—EKPT model, multiple learning factors, English online teaching, prediction and analysis

1 Introduction

With the development of artificial intelligence technology and computer science technology, the application of online learning system is becoming more and more popular, and it is welcomed by many learners. The online learning system not only provides a wealth of learning functions, but also has a wealth of resource data with the help of cloud technology, which can provide learners with personalized learning support [1]. At present, there are two typical online learning systems in China, including online Massive Open Online Courses (MOOC) and online judging system. The online learning system provides learners with rich curriculum resources through computer technology and big data technology, including functional services such as teaching courses, practice tests, and ability assessments [2]. Although the online learning system has been applied in schools at all stages of the country, it provides important convenience for students' learning. However, due to the lack of effective teaching supervision, the truancy rate of online course teaching is generally high. Therefore, personalized learning services are proposed to improve students' learning enthusiasm and enhance the learning experience effect in the course [3]. In the construction of the online English course resource platform, the core of personalized learning lies in the diagnosis of knowledge level. By building a knowledge learning tracking model, it can dynamically grasp the knowledge level of learners and provide learners with rich personalized learning support.

2 Related work

With the development of computer science and technology, neural network algorithms have been widely used in various fields. Domestic and foreign researchers have done a lot of research in this area. Sun et al. A deep learning algorithm is proposed to predict the current energy consumption and the future of green energy development. The experimental results show that the future green energy consumption in 2030 is expected to be about 78.25 EJ, accounting for 56% of the total average energy consumption in 2045 [4]. Monga et al. Discovering the future development and practical deployment of deep networks is still hindered by their black-box nature. A deployment method is proposed to develop fast neural network approximations with sparse coding. It turns out that the growing popularity of deploying deep networks is partly due to its potential to develop efficient, high-performance (but interpretable) network architectures from sizable training sets [5]. To effectively predict electrical loads, Chafi et al. A short-term power load forecasting method based on neural network and particle swarm optimization algorithm is proposed. The simulation results reflect the ability of the method to accurately predict the power load [6]. When establishing the mathematical model of the reduction process of carbon-containing pellets, Zhang et al. used MATLAB software to develop and train a feedforward backpropagation neural network model in order to obtain sufficient data to build a neural network. The results show that the established neural network model has high applicability [7]. In order to study the classroom student management assistant system, Nie et al. An intelligent analysis system of classroom students' state based on neural network technology and emotion feature recognition algorithm is constructed. The results show that the proposed model has good computational performance and prediction accuracy [8]. Li et al. Two mainstream generative models for deep learning, VAE and Gan, are found to have obvious flaws. The acvae-pggan network model is proposed, which jointly learns images with feature labels during training, so that image generation can be conditioned on custom features. The experimental results show that the improved network model proposed in this paper improves the stability of training, and effectively improves the resolution of generated images and the number of running frames [9]. To explore the application of deep learning algorithms in the field of reservoir operations, Zhang et al. used recurrent neural networks and long-term short-term memory to predict the outflow of

Xiluodu Reservoir. The results show that the number of iterations and the number of hidden nodes mainly affect the model accuracy. The former has a greater impact than the latter. The batch size mainly affects the computation speed [10]. In order to improve the effect of enterprise supply chain risk assessment, Lus et al. proposed a multi-level inventory control model based on Coordination Center Inventory and other retailers' purchasing/relocation strategy models. The research results show that the model proposed in this paper has certain effects [11]. Zhang et al. It is found that the traditional English test and the current test system can no longer meet the demand for English test in the education industry. A hierarchical network management model is proposed. The research results show that the proposed intelligent model and algorithm are completely feasible and effective [12]. Wang et al. A model suitable for English education is designed based on neural network algorithm. Experiments show that the system constructed by the audio-visual fusion method based on convolutional neural network can significantly improve the performance, and its recognition error rate is relatively reduced by about 15% [13].

With the popularization of online learning systems, domestic and foreign experts have conducted in-depth research on educational learning models. United States Tennis Association, etc. In order to efficiently retrieve educational resources, it is used as a search engine in the field of education. Experimental results show that a general-purpose and query-dependent ranking model trained by the LTR method can generate high efficiency in educational search and lead to a better learning experience [14]. Luch et al. Discovering the application of computer algorithms and intelligent recognition in distance education has become the norm. Based on machine learning technology, combined with intelligent image recognition technology, it can identify the status and expressions of students in distance education classrooms. The results show that the collected data is used to test and analyze the system, verifying the feasibility and accuracy of the system [15]. In order to match the most suitable sound-absorbing material and the most satisfactory sound-absorbing performance according to the noise spectrum in different practical applications, Wang y et al. used a multi-population genetic algorithm to optimize the parameters of ordinary porous sound-absorbing structures. The results show that the optimization results of the multi-population genetic algorithm are significantly better than the standard genetic algorithm in terms of sound absorption performance and sound absorption bandwidth [16]. Wang He et al. A model suitable for English education is designed based on neural network algorithm. Experiments show that a system built with a convolution -based audio-visual fusion method can significantly improve performance, with a relatively lower recognition error rate of around 15% [17]. In order to improve teaching intelligence, Ma w et al. constructed an auxiliary teaching system based on computer artificial intelligence and neural network on the basis of traditional teaching mode. The results show that the system constructed in this paper has good performance and can provide a theoretical reference for related research [18].

It can be seen from domestic related research that computer neural network technology has a wide range of applications in many fields. The application of online education system can significantly improve the effect of online education and provide important theoretical reference for the development of modern education.

3 Construction of EKPT model of English teaching curriculum resources based on multiple learning objectives

3.1 Constructing the EKPT model of curriculum resources combined with learning factors

The multi-objective EKPT model of English teaching course resources are constructed by using the English online learning system. Through the dynamic monitoring of the entire learning process of the students, the diagnosis of the learning status is realized. The core of English course resource model construction is to provide students with personalized learning services and to effectively evaluate students' knowledge and ability levels. The diagnosis of multifactorial learning processes is complex, and multiple characteristics can affect students' learning factors. Therefore, the construction of the EKPT model will go deep into the entire learning process, and the model-related features will be constructed from two levels of students and exercises. The construction of the system model lies in the diagnosis of knowledge level. In the construction of the EKPT model, the diagnosis of knowledge level is shown in Figure 1.

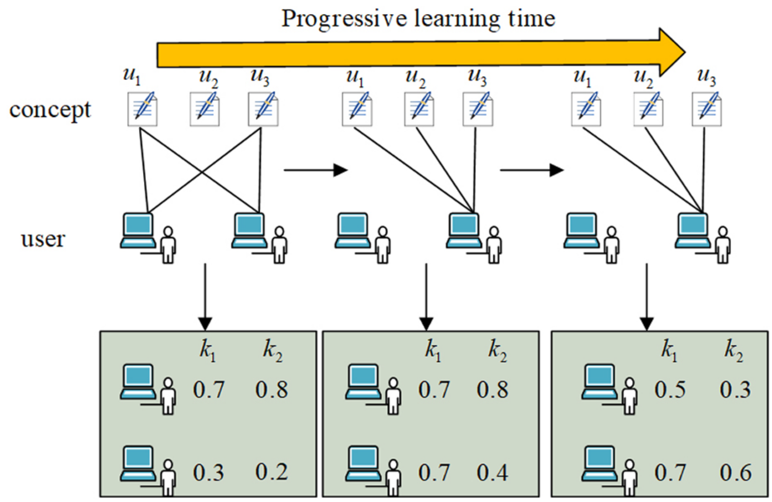


Fig. 1. Schematic diagram of student status diagnosis

Figure 1 shows the student's learning process by studying and doing questions over a three-month period. These two concepts are related to the question, u_1 Level in function k_1 from 0.7 to 0.3. In order to solve this problem, it is necessary to quantitatively describe the student's state through the relevant diagnosis model, and the data mining model can better mine the student's learning state by referring to the diagnosis process and the score prediction task. The construction of the EKPT model of curriculum resources integrating learning factors includes three processes: probability modeling, topic prior modeling and student prior modeling. The structural framework of the EKPT model ensemble learning factor is shown in Figure 2.

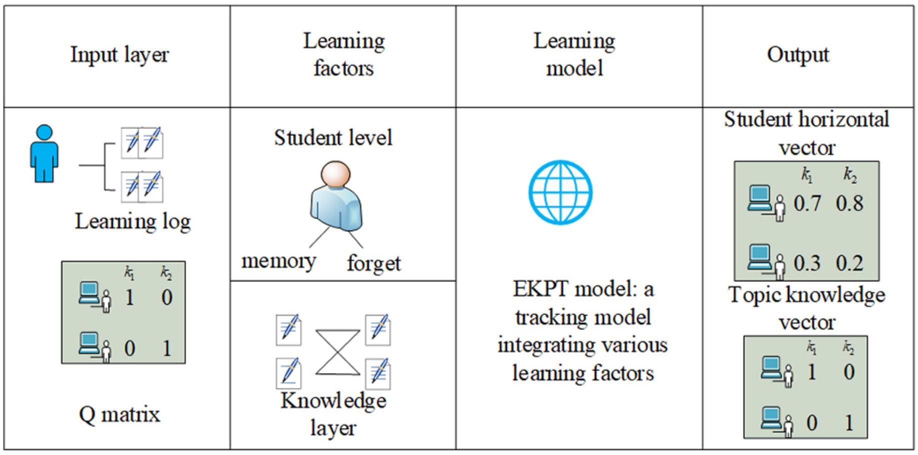


Fig. 2. The structural principle framework of the EKPT model integrating learning factors

In the construction of the probability model of learning behavior, the topic is set as j, student i, is the N total number of students, M is the number of topics, is the K number of knowledge concepts T, and is the number of time windows. According to the mastery of subject knowledge vector and the ability level of students, a probability model of learning behavior is constructed, and the conditional probability of learning log tensor is R shown in formula (1).

$$p(R \geq |U,V,b) = \prod_{t=1}^{T}\prod_{i=1}^{N}\prod_{j=1}^{M}\left[\mathbb{N}(R_{ij}^{t}\left|\left\langle U_i^t, V_j\right\rangle - b_j, \sigma_R^2)\right.\right]^{I_{ij}^{t}} \tag{1}$$

In equation (1), I denoting the tensor, the $\mathbb{N}(\mu,\sigma^2)$ normal distribution, μ is the mean, and σ^2 is the variance. In the learning behavior model, if i the time of the student learning the topic j is 11, then there is t. Otherwise, t it means that the $I_{ij}^t = 1$ student $I_{ij}^t = 0$ has the knowledge concept level vector $U_i^t \in \mathbb{R}^{K\times 1}$ at the moment i, which is t the knowledge vector of the topic about the concept. K At the same time, j indicate the difficulty of the question. In the construction of the learning model, in order to further grasp the students' learning dynamics and ability level, it is assumed that the students' ability to learn concepts will change with the change of their own abilities over time, and the students' knowledge level can be expressed in time. is a matrix, as shown in formula (2)

$$U = \{U^1, \ldots, U^t, \ldots, U^T\} \tag{2}$$

By constructing a matrix of students' learning knowledge level and using the function formula of formula (1), the expression of students' learning behavior factors can be realized.

When constructing topic prior models, partial ordinal and related factors need to be considered. In the construction of the learning probability model, V each dimension of the topic matrix and student tensor U cannot be associated with the knowledge concept.

Therefore, topic knowledge association Q matrices are combined and projected into a specific knowledge space. However, there are two problems with this approach. This Q matrix has the error of teacher's subjective labeling, and the labeling is difficult to adapt to the probability model. In this regard, the EKPT model adopts the partial order learning scheme to solve the problem, improves the Q matrix definition, and defines the partial order relationship of knowledge concepts, as shown in formula (3).

$$\begin{aligned}&\forall p,q\in K, p\neq q, \text{if } Q_{jq}=1 \text{ and } Q_{jp}=0 \Rightarrow q >_j^+ p,\\&\forall p,q\in K, p\neq q, \text{if } Q_{jq}=1 \text{ and } Q_{jp}=1 \Rightarrow q \not>_j^+ p,\\&\forall p,q\in K, p\neq q, \text{if } Q_{jq}=0 \text{ and } Q_{jp}=0 \Rightarrow q \not>_j^+ p,\end{aligned} \tag{3}$$

In formula (3), it $Q_{jq} = 1$ means that the topic is related to the concept of knowledge, and $Q_{jq} = 0$ it means that the topic has nothing to do with knowledge, which $Q_{jq} = 0$ is a partial order relationship. Comparable sets can be constructed through a partial order relation, as shown in Equation (4).

$$D_Q = \left\{(j,q,p)\middle| q >_j^+ p\right\} \tag{4}$$

The problem of labeling coefficients of traditional matrices can be solved by constructing comparable sets with partial order relation Q. Combining the likelihood function, partial order probability, and Gaussian prior with mean 0, the topic can be projected into the knowledge space of specific meaning. The problem of overfitting can be solved by adding a Gaussian prior. However, using only Gaussian priors can avoid overfitting problems, but learning data sparse can affect model performance. Therefore, relevant factors should be considered to guarantee the performance of the model.

In the processing of relevant factors, it is assumed that the knowledge vector information j of the topic and the adjacent topics N_{V_j} are jointly affected, and the expression is shown in Equation (5).

$$V_j = \sum_{I\in N_{V_j}} \omega(j,l)\times V_1 + \theta_V, \theta_V \sim \mathbb{N}(0,\sigma_V^2) \tag{5}$$

In Equation (5), $\omega(j,l)$ is the influence weight, which defines that the influence of the neighbor problem is consistent with the influence of the target problem j. After transforming Equation (5) into Equation (6), the performance of the model can be guaranteed.

$$P(V) = \prod_{j=1}^{M} \mathbb{N}\left(\frac{1}{\left|N_{V_j}\right|}\sum_{I\in N_{V_j}} V_i, \sigma_V^2\right) \tag{6}$$

When constructing student prior modeling, the model is constructed in combination with the student's knowledge level tensor U. The knowledge level tensor is shown in formula (7).

$$p(U_i^t) = \mathbb{N}(U_i^t \left| \bar{U}_i^t, \sigma_U^2 I \right.), \text{where } \bar{U}_i^t = \left\{ \bar{U}_{i1}^t, \bar{U}_{i2}^t, \ldots \bar{U}_{iK}^t \right\} \tag{7}$$

In formula (7), U_i^t is the knowledge level vector of the students at that time, U_i^t obeys $\bar{U}_i^t$, and $\sigma_U^2 I$ is the normal distribution of variance. At the same time, the definition of memory factor is shown in formula (8).

$$L_{ik}^t(*) = U_{ik}^{t-1} \frac{Df_{ik}^t}{f_{ik}^t + r} \tag{8}$$

In Equation (8), f_{ik}^t is the number of times the student learns the knowledge concept K, r and D represents the hyperparameter. After a certain number of practices, the students' concept increase K shows the memory factor, and vice versa is the forgetting factor. The forgetting factor is shown in formula (9).

$$F_{ik}^t(*) = U_{ik}^{t-1} e^{-\frac{\Delta t}{s}} \tag{9}$$

In Equation (9), S is the hyperparameter and Δt is the knowledge interval. When it t is 1, it means that the learning is not in progress, and the students' knowledge is uniform in this state. It is assumed that the knowledge level of students obeys a Gaussian distribution with a mean of 0. Combining Equations (7), (8) and (9), the prior distribution of the student level tensor is obtained U, as shown in Equation (10).

$$p(U \left| \sigma_U^2, \sigma_{U1}^2 \right.) = \prod_{i=1}^{N} \mathbb{N}(U_i^1 \left| 0, \sigma_{U1}^2 I \right.) \prod_{t=2}^{T} \mathbb{N}(U_i^t \left| \bar{U}_i^t, \sigma_{U1}^2 I \right.) \tag{10}$$

3.2 Construction of EKPT model of multi-learning objective curriculum resources

By constructing an EKPT model of course resources, the diagnosis of multiple learning objectives can be achieved. Multi-objective learning models include knowledge ability prediction diagnosis model, performance prediction diagnosis model and visual result diagnosis model. The application of the multi-objective EKPT model in English course resources can be achieved through the construction of three learning objective models. In the construction of the EKPT model of course resources, it can be known that the students' i current personalized learning parameters are a_i, and the knowledge level matrix is U_i^T. In the construction of knowledge and ability predictive diagnostic models, $L_{ik}^t(*)$ memory factors and forgetting factors can be calculated. Equations (8) and (9) $L_{ik}^t(*)$ can be used to predict students' mastery of knowledge concepts. $t + 1$ The expression of knowledge and ability prediction is shown in Eq. (11).

$$\begin{aligned} \hat{U}_i^{(T+1)} &= \left\{ \hat{U}_{i1}^{(T+1)}, \hat{U}_{i2}^{(T+1)}, \ldots, \hat{U}_{iK}^{(T+1)} \right\}, \\ \hat{U}_i^{(T+1)} &\approx a_i U_{ik}^T \frac{Df_{ik}^{T+1}}{f_{ik}^{T+1}} + (1 - a_i) U_{ik}^T e^{-\frac{\Delta(T+1)}{s}} \end{aligned} \tag{11}$$

In Eq. (11), the quantity is $\hat{U}_i^{(T+1)}$ an estimate of the knowledge ability of the knowledge concept f_{ik}^{T+1} for the student to i stay $t+1$ at any time. K Frequency and quantity of knowledge for $\Delta(T+1)$ students who k have been training. Intervals are studied $T+1$ for $T+1$ students closest to this knowledge concept. k Through the construction of knowledge ability prediction model, it is possible to predict the degree of students' mastery of knowledge concepts in a certain period of time. Figure 3 is a schematic diagram of the knowledge ability prediction and diagnosis model.

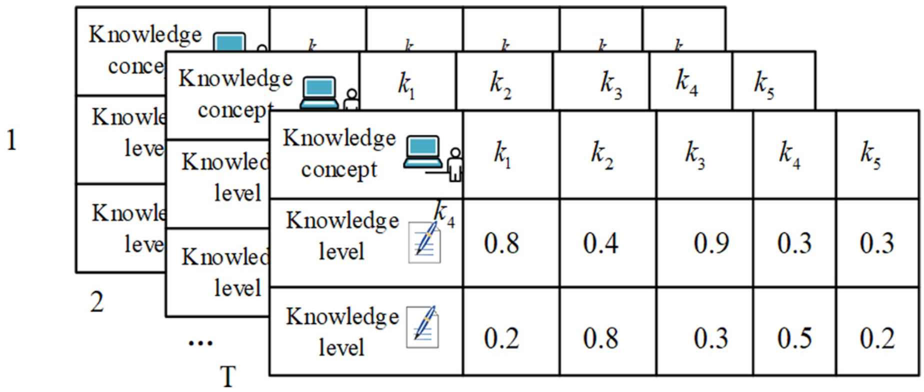


Fig. 3. Schematic diagram of the knowledge ability prediction and diagnosis model

In the construction of the grade prediction and diagnosis model, through the mastery of the students' knowledge level, the effective prediction of grades can be achieved without practice. Among them, after the students i practice j the multi-objective EKPT model training, they can get the j Difficulty coefficient of b_j and knowledge vector of the question V_j. At this point, we can use Equation (11) to pass the above process on the $T+1$ Knowledge level vector once $U_i^{(T+1)}$, and students can get the score expression i for the question j 's score as shown in Equation (12).

$$\hat{R}_{ij}^{(T+1)} \approx \left\langle U_i^{(T+1)}, V_j \right\rangle - b_j \tag{12}$$

In Equation (12), considering that the model may appear during training $[0, 1]$, Equation (12) can be modified to better predict students' academic performance, as shown in Equation (13).

$$\hat{R}_{ij}^{(T+1)} \begin{cases} \hat{R}_{ij}^{(T+1)} & \text{if } 0 \le \hat{R}_{ij}^{(T+1)} \le 1, \\ 0 & \text{if } \hat{R}_{ij}^{(T+1)} < 0, \\ 1 & \text{if } \hat{R}_{ij}^{(T+1)} > 1. \end{cases} \tag{13}$$

In formula (13), the range of training values is adjusted to better predict students' practice performance. The predicted results of the scores will be used as $T+1$ a reflection of the students' achievement of mastering relevant knowledge and concepts through practice training at any time. The schematic diagram of the performance prediction and diagnosis model is shown in Figure 4.

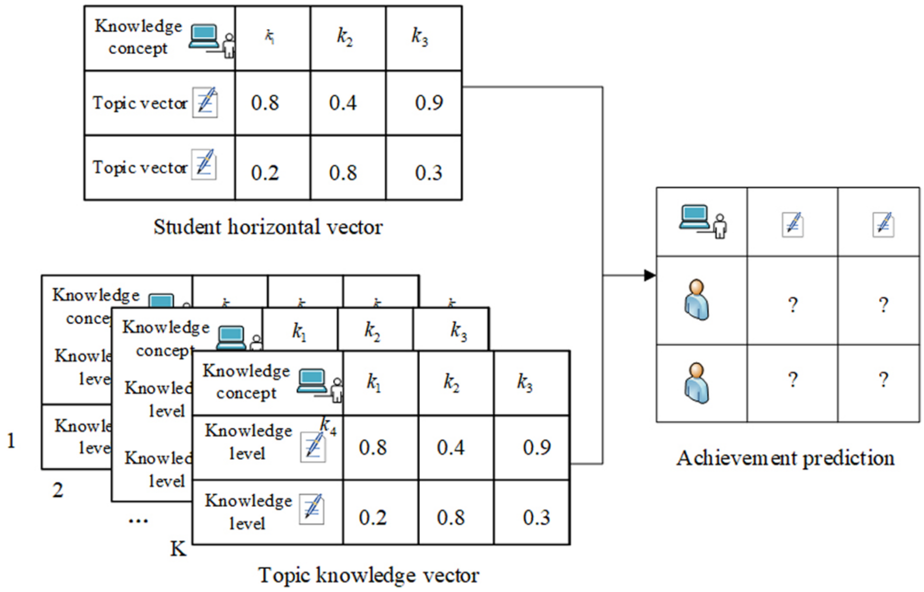


Fig. 4. Is a schematic diagram of the performance prediction and diagnosis model?

In the construction of the visualization results diagnosis model, the visualization of the target results can directly reflect the students' learning status. The definition and quantification of visual outcome diagnostic models are affected by many learning factors, such as memory forgetting factors, knowledge-related factors, etc. Therefore, the construction of the diagnostic model of the visualization results can realize two aspects of visualization. For students, *i* the forgetting curve and learning curve can be combined, and the visual model can analyze the change of students' knowledge level and the relationship between students' learning behavior. At the same time, according to the mastery of the relevant characteristics of the subject at the knowledge level, the model can *i* realize the visualization of students' sports training through the position of each subject in the knowledge space. Figure 5 is a schematic diagram of a knowledge-level visualization result diagnosis model.

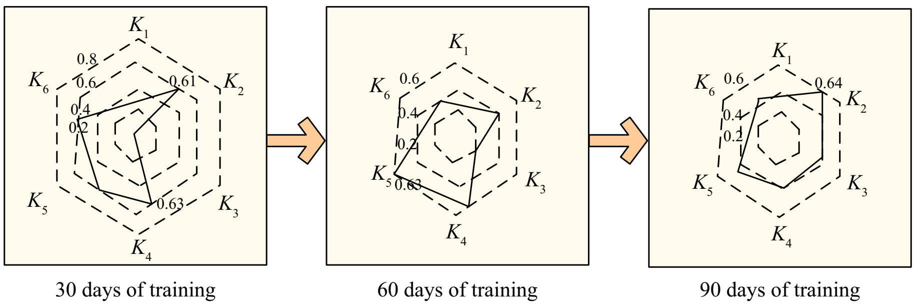


Fig. 5. Is a schematic diagram of the visual result diagnosis model

4 Experimental training of EKPT model with multiple learning objectives

4.1 EKPT model training with multiple learning objectives

To further evaluate the application performance of the proposed learning model, the performance of the proposed learning model will be tested through three educational application tasks. The three training tasks include prediction of students' knowledge ability, prediction of students' academic performance and diagnosis of visual results. Experimental training will complete the experimental tasks through four experimental datasets, including English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset. The information parameters of the four datasets are shown in the Figure 6.

Dataset	Training log	Test log	#student	#exercises	Time windows	Knowledge concept
Math1	521,248	74,464	9,308	68	4	12
Math2	347,424	18,312	1,306	290	10	13
Assist	263,327	43,888	7197	3245	7	20
Adaptive	229,848	38,308	3,217	411	7	12

Fig. 6. Shows the basic information of the four datasets

In the experimental parameter settings, English1 dataset, English2 dataset and auxiliary dataset have 4, 10, and 7 time points. The former time dataset is used as the training set, and the latter time is used as the test set. In the experimental test, we chose the benchmark method of educational psychology for comparison. The specific experimental parameter settings are shown in Table 1.

Table 1. Basic parameter information of how S is experimentally tested

Experimental Variable Parameter Index	Index Value
memory factor L_{ik}^{t} (*)	$D = 2$
forgetting factor F_{ik}^{t} (*)	$S = 5$
Regularization Hyperparameters λ_{UI}	0.01
Values for the four datasets λ_P	1.5, 1, 2, 2
Values for the four datasets λ_U	3, 1, 2, 1.5
Values for the four datasets λ_S	0.02, 0.01, 0.005, 0.1

In the experimental training of students' knowledge ability prediction, considering the uncertainty of students' knowledge ability development, an EKPT model is proposed to predict students' knowledge level at a certain moment in the future. At $T + 1$

present, students 'mastery of a knowledge concepts k is better than students' b. In the experimental test, a the probability of topics related to b knowledge concepts are also significantly better than that of students k. Therefore, the consistency index is used to rank the training results in training, where K it represents the number of concepts the student has mastered. In order to improve the performance of the proposed learning model, the experiments involve the exercise-aware knowledge tracing (KPT) model, the (Program bayesian Probabilistic Matrix Factorization, QPMF) model, the (Item Response Theory, IRT) model and (Bayesian Knowledge Tracing, BKT) model, (Deterministic Inputs, Noisy "And" gate, DINA) model. As shown in Figure 7, the knowledge ability prediction results of the multi-learning model are shown.

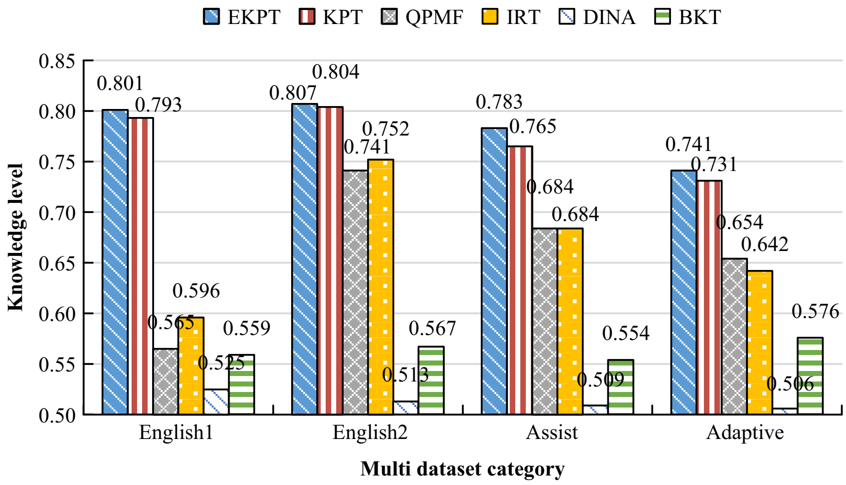
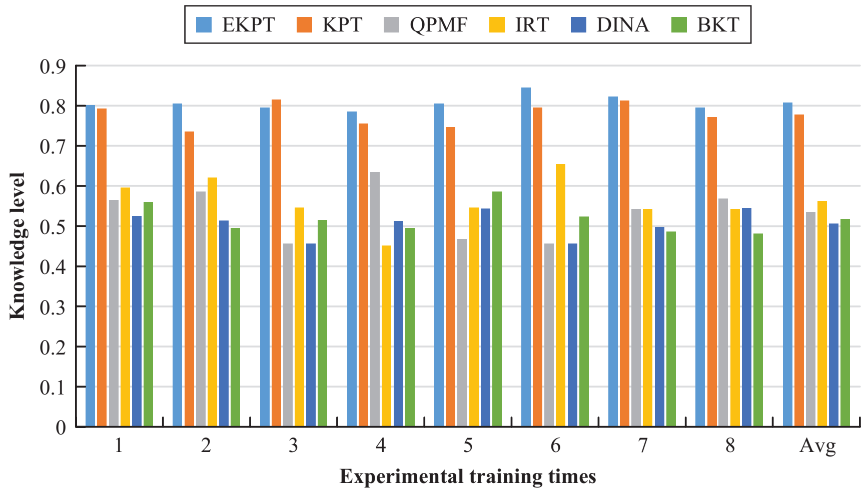
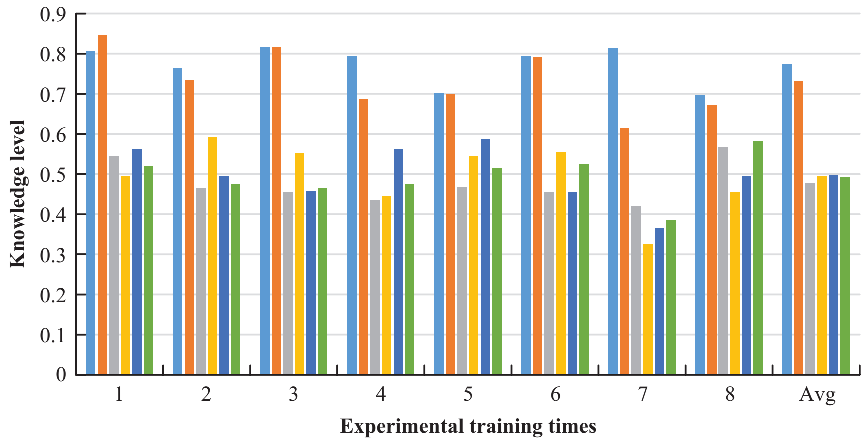


Fig. 7. Knowledge ability prediction results of the multi-learning model

Figure 7 shows the knowledge ability prediction results of multiple models. From the experimental test data, it can be seen that the proposed EKPT learning model has excellent knowledge level prediction performance in the experimental training of the four datasets, and the predicted probability value is the best. The prediction results of English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.801, 0.807, 0.783 and 0.741, respectively. The KPT learning model ranks second in knowledge ability prediction. The prediction results of English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.793, 0.804, 0.765 and 0.731, respectively. The Dina learning model is the worst predictor of knowledge and ability. The prediction results for English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.525, 0.513, 0.509 and 0.506, respectively. Meanwhile, to further examine the knowledge ability prediction performance of the proposed EKPT learning model, multiple experimental tests will be conducted to evaluate the performance of each model, as shown in Figure 8.



(a) Math1 data set

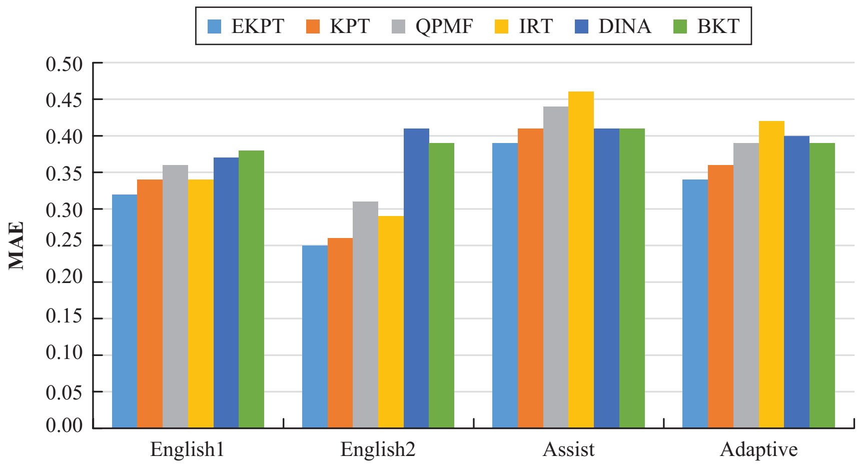


(b) Math2 data set

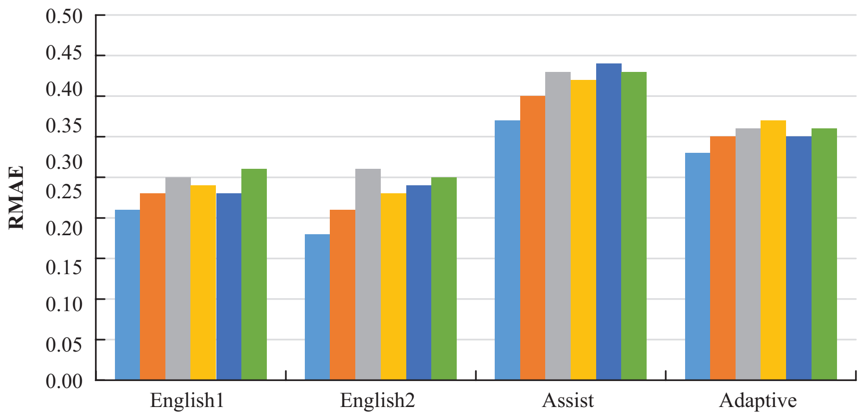
Fig. 8. Shows the results of multiple training sessions of the learned model

Figure 8 shows the results of multiple training sessions of the learned model. From the experimental test data, it can be seen that the proposed EKPT learning model has excellent knowledge ability prediction results on both English1 dataset and English2 dataset, and the prediction results are the best in multi-learning model training. In Figure 8(a), the EKPT model has more stable training performance than other learned models in training on the English1 dataset. The lowest predicted value was 0.781, the highest was 0.831, and the average was 0.803. The KPT learning model ranks second in knowledge and ability prediction. The training prediction results fluctuate greatly, the lowest predicted value is 0.721, the highest is 0.812, and the average is 0.789. It can be seen that the EKPT model has the best stable performance and the best test mean performance. Figure 8(b) shows the training results of multiple models on the English2 dataset. It can be seen that the EKPT model has excellent performance and stability. The highest estimate was 0.812, the lowest was 0.698, and the average was 0.782. The mean values of KPT, QPMF, I RT, Dina and BKT were 0.723, 0.481, 0.499, 0.498 and 0.493, respectively. It can be seen that the EKPT model combines knowledge-related factors, memory and forgetting factors in the experimental training, which can enable the EJOT model to better predict the knowledge level of students, while the traditional QMRT is a static model and does not fully consider the learning process. dynamic factors, perform worst in predicting knowledge and ability. It can be seen that the proposed EKPT model performs the best in knowledge ability prediction.

In student achievement prediction, mean absolute error (MAE) and root mean square error (root-mean-square error, RMSE) to test students' grades, $T+1$ the lower the error value, the more accurate the grade prediction. The performance prediction results are shown in Figure 9.



(a) Multi dataset category



(b) Multi dataset category

Fig. 9. Shows the prediction results of student grades from the multi-learning model

Figure 9 shows student performance prediction results for multiple learning models. In the experimental training of the six learning models, the EKPT model has the best performance and the smallest error. It shows that the EKPT model has obvious advantages in diagnosing students' knowledge level by introducing knowledge-related factors, memory and forgetting factors. In Figure 9(a), the EKPT model has the smallest MAE error value, and the MAE values of English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.32, 0.25, 0.39 and 0.34, respectively. The error performance of the KPT model is second, with Mae error values of 0.34, 0.26, 0.41 and 0.36, respectively. Figure 9(b) shows the RMAE prediction results. The EKPT model performed the best on the four data tests. The RMAE values for English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.21, 0.18, 0.32 and 0.28, respectively. The Dina model has the worst predictive performance. The main reason is that the Dina model is a static model and does not fully consider the learner's variables. Their RMAE values were 0.23, 0.24, 0.39 and 0.30, respectively. It can be seen that the proposed EKPT model has excellent performance in predicting students' grades.

In the experimental training of visual outcome diagnosis, the EKPT model can analyze the entire learning process of students. Through the correlation between students' knowledge level and learning behavior, the visual analysis of students' learning process can be realized, as shown in Figure 9.

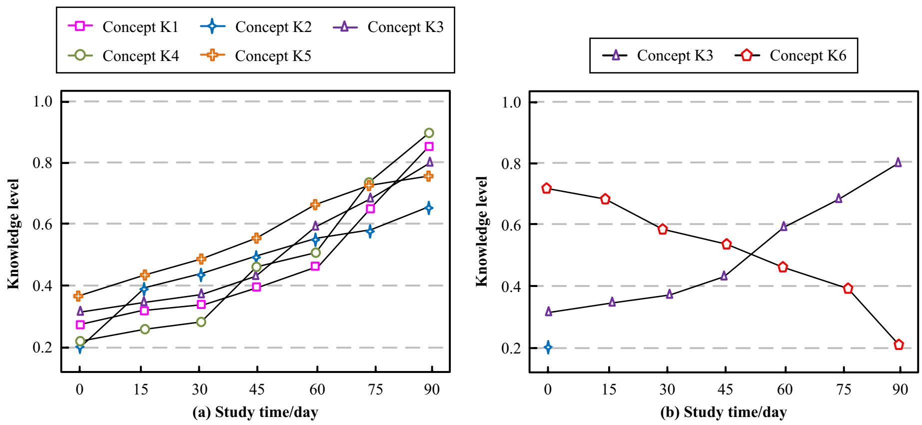


Fig. 10. Visualization results of three-month students' conceptual learning in the English1 dataset

Figure 10 shows the visualization results for three months of student knowledge concepts in the English1 dataset. In Figure 10(a), with the increase of students' three-month study time, the students' learning levels of the five knowledge concepts have improved to varying degrees. In the study of English grammar concept K4, the students' English grammar concept learning level improved from 0.21 to 0.85 after three months. In Figure 10(b), the students did not review the concept K6 for three months, and the students' related knowledge level also dropped from 0.67 at the beginning to 0.20 after three months. It can be explained that with the help of the EKPT model, the visual analysis of the students' learning process can be realized.

At the same time, the EKPT model can realize the associated data mining between topics, helping learners to better grasp the effect of the model. Therefore, the EKPT model and the KPT model are selected here to participate in the experimental training. The topic cluster analysis is shown in Figure 11.

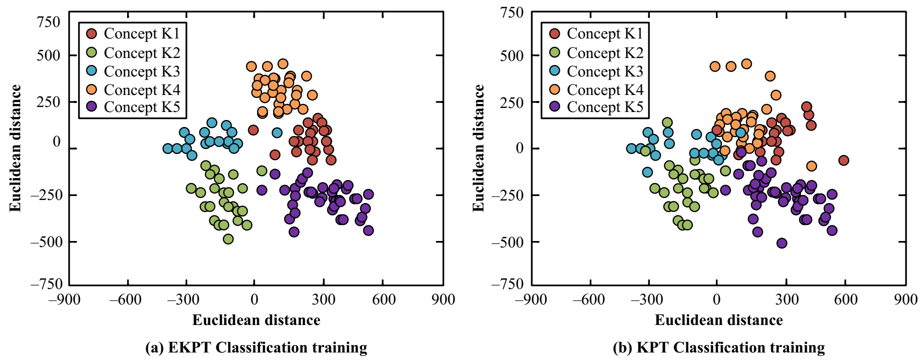


Fig. 11. Cluster analysis results of model topics

Figure 11 shows the cluster analysis results of the English learning model1. The principle of model cluster analysis is to divide English topics with the same concept into a group, and use Euclidean distance to construct a two-dimensional surface distance. Figure 11(a) shows the clustering results for the subjects of the EKPT model. Topics are clearly divided according to the same concept, and topics with the same concept can be reasonably classified. Figure 11(b) shows the results of topic clustering using the KPT model. There is no clear division of the same concept topics, and each topic is widely distributed. It shows that the EKPT model has good topic clustering performance, which proves that the EKPT model can well combine knowledge-related factors to build a learning model and meet the construction needs of an online English course resource platform.

4.2 Analysis of the experimental results of the EKPT model with multiple learning objectives

Compared with traditional IRT, BKT, DINA, PMF and other models, the proposed EKPT model has more intuitive performance in the overall visual learning prediction. Especially in the classification tests of students' English scores, English learning types, etc., the model has a good performance effect. In the construction of the English online platform, the model can accurately predict and analyze students' grades, learning status and knowledge content. Through the analysis results of the model, the relevant data results are fed back to the online learning center, which can choose more flexible learning strategies and learning content for students, which is more conducive to the development and progress of students.

5 Conclusion

With the development of computer science and technology, online education provides learners with more flexible and convenient learning services. In the construction of the English online teaching system, in order to better provide students with personalized learning support and improve the functional effect of the online English course resource platform. A knowledge tracking model integrating multi-objective learning factors is proposed. According to the subject knowledge correlation matrix, the spatial projection of subject information is realized. The experimental training results show that the EKPT model performs best in the prediction training of students' knowledge and ability. The prediction results of English1 dataset, English2 dataset, auxiliary dataset and adaptive dataset are 0.801, 0.807, 0.783 and 0.741, respectively. The proposed EKPT model has the best experimental training performance in performance prediction and diagnosis as well as topic clustering training. Therefore, the EKPT model can well meet the construction needs of the English online teaching course resource platform and improve the students' learning experience. The research content has important reference value for the application of computer big data technology in educational environment. However, this study also has some shortcomings. Online learning scenarios are complex. We should study the change of knowledge state according to the needs of students, which is more in line with the actual needs of users.

5.1 Funds

The research results are: the key teaching research project of the school-level undergraduate teaching quality improvement plan – Study on the ideological and political teaching design of college English courses based on SPOC (2021jyxm18) and the school- level scientific research project of Anhui Polytechnic University – Zhu Guangqian's aesthetic translation research (xjky20191103).

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Article submitted 2022-09-19. Resubmitted 2022-11-02. Final acceptance 2022-11-04. Final version published as submitted by the authors.