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Research on Learning Path Optimization Strategies of Blended Teaching Learning Path for English Majors Based on Multilayer Perceptual Machine Model

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Abstract In this paper, we combine the interactive feature capture and basic feature capture modules of multilayer perceptron to extract and fuse features of knowledge concepts. With the help of cluster search algorithm and softmax way to optimize the learning path, the learning path recommendation model based on multilayer perceptron is proposed. Suitable datasets and research objects are selected, and the effectiveness of the blended teaching mode supported by the TMLPE model is examined through experiments. The TMLPE model scores higher than the baseline model in MRR and NDCG indexes, and the Er index is 12.23% higher than that of the ELPRKG model with the second best performance, which is capable of generating accurate and diversified learning paths for learners. The different models of teaching activities show significant differences at the 0.01 level ($p=0.00<0.01$) in the dimensions of learners' personalized learning goals, and the means of the experimental group are all greater than those of the control group, with a comparison of the mean values of 3.95>3.42, 4.06>3.15, and 3.96>3.11. The p-values of the personalized learning needs and the personalized learning goals as a whole are all less than 0.05 and the R-values are all in the interval of 0.5 to 1.0. The intelligent recommender system based on the multilayer perceptual machine model in this paper can effectively meet the learning needs of different students, and has a positive role in promoting the development of blended teaching for English majors.

Index Terms multilayer perceptron, cluster search algorithm, learning path recommendation, English major, blended teaching

I. Introduction

With the rapid development of information technology and the popularization of the Internet, the traditional teaching mode is undergoing a revolutionary change. In the field of higher education, blended teaching mode, as a new type of teaching mode integrating traditional face-to-face teaching and online teaching, has attracted much attention and has been gradually applied in the teaching practice of various disciplines [1]. As an important foreign language, English plays a crucial role in higher education, and is of great significance in cultivating students' language proficiency, cross-cultural communication skills and comprehensive literacy [2].

Under the traditional English teaching mode, students often face problems such as limited classroom time, limited teaching resources, and insufficient interest in learning, and the teaching effect is hardly satisfactory [3], [4]. And the introduction of blended teaching mode provides a new way to solve these problems. Blended teaching evolved from the concept of blended learning, emphasizing the joint role of “technology media” and “instructional design”, aiming at combining the advantages of traditional face-to-face learning mode and modern distance learning mode, and complementing each other's strengths [5]-[7]. By combining online and offline teaching resources, blended teaching mode can flexibly arrange classroom time, improve students' learning efficiency and interest, enrich teaching resources, promote students' independent learning and cooperative learning, so as to better meet students' individualized learning needs and improve the quality and effect of English teaching [8]-[11]. In addition, blended teaching breaks through the traditional teaching restrictions on time and space, and teaching and learning do not always have to happen at the same time and place, expanding the time and space for teaching and learning [12], [13]. In order to further help students master the required English proficiency, the reform and optimization of English blended teaching in colleges and universities can be started from by exploring the application path of English blended teaching in colleges and universities with a view to constructing a more reasonable English teaching model [14]-[16].

In this paper, we propose a learning path recommendation model based on multilayer perceptual machine for the functional requirements of intelligent recommendation system. Combining the interactive feature capture module and the basic feature capture module, the association between knowledge points and students' learning needs are deeply explored. The learning path is optimized using cluster search algorithm, and the knowledge concept with maximum probability of each time step is obtained by softmax. Verify the effectiveness and feasibility of the proposed model by combining data set experiments and specific case studies. Design teaching experiments to explore the application effect of blended teaching mode based on intelligent recommender system.

II. English Learning Path Optimization for College Students Based on Multilayer Perceptual Machine Model

In today's digital education era, blended teaching mode integrates the flexibility of online learning with the interactivity of offline learning, and has become a popular research direction in the field of education. For the teaching of English majors, how to provide students with personalized learning paths in order to improve the learning effect and interest is an urgent problem to be solved.

II. A. Research on Artificial Intelligence Optimizing the Personalized Path of College Students' English Learning

Artificial intelligence, combined with big data and intelligent algorithms, can accurately analyze each college student's learning interest, knowledge level, etc., so as to create personalized learning resources for them. Artificial intelligence can monitor the learning situation of college students in real time and continuously optimize the learning resources according to their reading time, reading volume and correctness rate, helping them to build up self-confidence and stimulate their learning interest in the learning process. Therefore, this personalized learning path can ensure the fairness of education.

II. A. 1) Analysis of student data

With the help of commonly used learning platforms can record the learning data of college students, such as the number of times a chapter has been studied in the last seven days, the average viewing time, and the names of the fastest and slowest students. These data reflect each student's effort value, learning interest, and difficulties.AI technology pushes the above data to teachers after in-depth analysis, so that teachers can explain the common difficulties in detail and supervise students with slow progress.AI technology accurately analyzes the learning data, which is a solid foundation for customizing exclusive learning programs.

II. A. 2) Intelligent Recommender System

Based on the results of the student data analysis mentioned above, the AI intelligent system uses deep learning algorithms to analyze the data of college students' reading interest, listening ability, writing ability, etc., and formulate personalized learning programs for them. The AI system pays attention to the students' learning progress in real time, and reminds the students of their progress and correctness while giving feedback to the teachers. It will automatically adjust the learning content and the difficulty level of the exercises so as to enhance the learning effect of the students. Therefore, AI's intelligent recommendation system can help college students maximize their sense of accomplishment.

II. B. Learning path recommendation model based on multilayer perceptron machine

The core of knowledge graph embedding is the scoring function, compared with simple models such as TransE, deep learning models are able to capture more complex features, however, a large portion of the relationships in the knowledge graph are simple linear relationships, which can be well scored by simple models, and with the increase of the number of layers, the deep learning model may not be as good as the simple model in terms of learning effect of the simple relationships, in order to ensure the loss of learning effect caused by the increase of the number of layers, this paper refers to the DeepE model using residual connection to solve this problem, and adopts the cluster search algorithm and softmax to optimize the learning path, and proposes the TMLPE learning path recommendation model.

II. B. 1) Interactive Feature Capture Module

The Interactive Feature Capture module consists of an MLP and a residual linkage, where each MLP layer is separated by a BN layer, a Dropout and an activation function layer (the activation function used here is ReLU). The interaction feature capture module cascades the head node embedding vectors and relation embedding vectors and then aggregates the information of the two, and inputs the aggregated information into an MLP module, so as to better capture the interaction features of the head nodes and relation nodes.

The head node embedding vector h and the relation embedding vector r are taken as inputs, and the output v_1 is obtained after feeding into the interactive feature capture module, which is denoted as $f(h,t)$. The specific definition is as in equation (1):

$$f(h,t) = BN([h \square t] + MLP([h \square t])) \tag{1}$$

where the $\square$ symbol denotes the cascade operation, i.e., connecting two tensors along the channel dimension; BN is batch normalization, which can solve the problem of difficult model training as the depth of the network is accelerated; and MLP is the multilayer perceptron, which is defined as in Eq. (2):

$$MLP^{(1)}(x) = \sigma\left(\left(Dropout\left(BN(W_1 x)\right)\right)\right) \tag{2}$$

where W_1 is the weight matrix and σ is the activation function (ReLU is used here). The above figure shows a single multilayer perceptron structure; the real case may consist of multiple multilayer perceptron structures.

The module combines the head node embedding vector h and the relation embedding vector r into a single vector after cascade operation, and then uses multiple multilayer perceptrons to capture the interaction features between the vectors, and finally obtains an output vector v_1.

II. B. 2) Basic Feature Capture Module

The basic feature capture model consists of an attention layer and an MLP. The head node embedding vector h and the relation embedding vector r are input into this module separately, and its specific structure is shown in Fig. 1. In order to better capture the respective basic features of the head node and the relation node, so the head node embedding vector and the relation node embedding vector are inputted into the MLP module to get the outputs respectively, and finally all the outputs are cascaded and aggregated to get the final output.

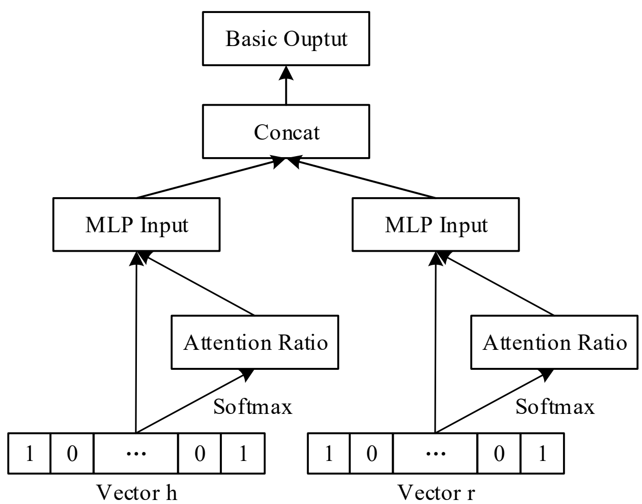


Figure 1: Basic Feature Capture Module

First, the head vector h and the relation vector r are passed through the attention layer to obtain their attention weights α_h and α_r, respectively, as in Eqs. (3) and (4):

$$\alpha_h = Attention(h) \tag{3}$$

$$\alpha_r = Attention(r) \tag{4}$$

In this, the attention layer uses an attention function (Softmax is used here) to get the attention weights. After obtaining the attention weights of h and r, the attention weights and the initial inputs h and r are input into a merge function, where the merge function chooses the cascade operation and the product of elements, which is used according to the experimental results to choose which one to use, to obtain the final inputs h_1 and r_1, with the specific formulas as in Eqs. (5) and (6):

$$h_1 = concat(h, \alpha_h)\ or\ mul(h, \alpha_h) \tag{5}$$

$$r_1 = concat(r, \alpha_r)\ or\ mul(r, \alpha_r) \tag{6}$$

Then the final inputs h_1 and r_1 are fed into the MLP layer to get their respective outputs. The basic feature capture model is slightly different from the MLP structure of the interactive feature capture model, which only adds Dropout, BN, and activation functions to the last linear layer, as shown in Equation (7):

$$MLP^{(2)}(x) = Dropout\left(BN\left(\sigma(W_n(...W_1 x))\right)\right) \tag{7}$$

Finally, the final output is obtained by cascading the outputs obtained from h and r, which is denoted as $g(h,t)$ and is defined as in Equation (8):

$$g(h,t) = MLP\left(Attention(h) \square Attention(r)\right) \tag{8}$$

The base feature capture module uses a structure consisting of an attention layer plus a multilayer perceptron layer to capture the base features of the head node embedding vector h and the relation embedding vector r, respectively, and finally uses a cascade operation to merge the two outputs to obtain the final output.

II. B. 3) Optimization of learning paths

In the face of the large and complex set of knowledge concepts in the learner graph information, how to accurately indicate the learning direction for the learners and provide a truly meaningful learning path planning is the focus of this research paper. Simply stacking all the relevant knowledge concepts together through deep learning models does not form an effective learning path. Because on the one hand, learners' time and energy are limited, and they cannot master all knowledge concepts in a short time. On the other hand, there exists a complex correlation between knowledge concepts, some knowledge concepts are the basis of other knowledge concepts, some are parallel or complementary, and this correlation determines the order and focus of learning.

In order to solve this problem, this paper adopts the cluster search algorithm to optimize the learning path. The core idea of the cluster search algorithm is to retain a certain number (e.g., 3-5) of the highest scoring knowledge concepts at each time step, which are considered to be the most urgent need for learners to pay attention to and master at the moment. In this way, this paper can ensure the diversity of learning paths while ensuring the quality of the selected paths. In addition to retaining the knowledge concepts with the highest scores, the knowledge concepts with the maximum probability for each time step are also obtained by softmax approach. The benefit of this approach is that it can more intuitively reflect the learner's learning focus at the current time step, thus providing a stronger basis for accurate planning of learning paths.

Ultimately, based on the sequential modification relationship and inclusion relationship between knowledge concepts, the precise learning path planning and fuzzy learning path planning can be generated for the learners by linking the topK knowledge concepts and the maximum probability knowledge concepts retained at each time step. Precise planning provides learners with clear learning goals and steps, while fuzzy planning provides learners with a wider range of learning options and exploration space. This dual-planning scheme is designed to meet the individual needs of learners in different learning stages and scenarios, thus enhancing their learning efficiency and effectiveness.

III. The optimization effect of multilayer perceptual machine model in the learning path of blended teaching for English majors

III. A. Analysis of model validity

III. A. 1) Data sets

In this paper, the MOOPer dataset released by OpenKG is used to evaluate the application effect of the TMLPE model.The MOOPer dataset is derived from the learners' online practice data of the EduCoder platform, in which the auxiliary information of the learners and the practice items (including the entities of courses, hands-on trainings, learning gates, knowledge points, etc.) is organized in the form of a knowledge graph. For the learning level interaction data in the MOOPer dataset, the first 10 learning records of learners are first selected to represent the learning path. Then the average length of the learner passing the level was taken as the time spent on learning the path, and the average rating of the learner passing the level was taken as the rating of the path. Then, based on the university's daily schedule of opening, examination, and vacation, February to March and September to October are set as the basic learning scenarios, April to May and November are set as the deepening learning scenarios, and June and December are set as the pre-test revision scenarios, while January, July to August, and the paths with abnormal learning duration are excluded. Finally, a dataset of 965.75 million learning paths is obtained with field information such as learning path sequence, learning date, learning duration, and learning scenario. Based on the original knowledge graph in the MOOPer dataset, the connection between entities is enriched according to the knowledge co-occurrence relationship of the knowledge point's first-modified-subsequent relationship knowledge co-occurrence relationship. At the same time, the information of practical training, courses and knowledge points are added to the level entities to enrich the background information of the level. The optimized knowledge graph contains 3956 level entities and 78,572 relationships, and each level entity has 10 attributes such as name, difficulty, number of points, and score rate.

III. A. 2) Assessment of indicators

In this study, Mean Reverse Ranking (MRR) and Normalized Discounted Cumulative Gain (NDCG) are used as evaluation metrics to assess the accuracy of the TMLPE model in learning path recommendation. Both metrics have been widely used to measure various sequence recommendation tasks, where MRR mainly indicates the location of the first correct path among the recommended learning paths; NDCG is used to measure the ranking quality of the list of K recommended learning paths.

In terms of the interpretability of path recommendation, no widely accepted evaluation criteria have yet emerged. Considering the specificity of the learning path recommendation task, this paper firstly fuses the fit score $sco_s(p_r)$ of the recommended path with the learning scenario, and the match score $sco_u(p_r)$ of the recommended path with the learner, to obtain the weighted score $sco(p_r)$ of the two; on the basis of which, we add the learner's acceptance score of the recommended path $sco_a(p_r)$, the total interpretable score E_r of the recommended path is obtained according to Eq. (9).

$$E_r = \frac{1}{2}\{sco_a(p_r) + sco(p_r)\} \tag{9}$$

The design of the learner acceptance metric is based on the assumption that the user's rating of the recommended items can measure the interpretability of the recommendation results to some extent. The acceptance score $sco_a(p_r)$ is calculated as shown in Equation (10), where I is the number of learners in the clustering cluster to which the target learner belongs with its distance within θ, p_r is the candidate learning path, p_i is the pre-existing learning paths of the similar members of the target learner $i(i \in I)$, lp is the length of the paths, r_{ij} is the learner i's rating of learning path j, and s_{p_r,p_i} is the path similarity.

$$sco_a(p_r) = \frac{1}{I}\sum_{i\in I}\sigma\left(\frac{\sum_{j\in J} r_{ij}}{\sqrt{1+(lp_i - lp_r)^2}} s_{p_r,p_i}\right) \tag{10}$$

III. A. 3) Analysis of controlled experiments

In order to evaluate the performance of the TMLPE model, this paper compares it with the baseline models (including the Clustering model, ACO model, and ELPRKG model), and the performance comparison results are shown in Table 1.

The scores of TMLPE model on MRR and NDCG metrics are 0.502 and 0.483, respectively, which are higher than those of the baseline model. The TMLPE model learns the semantic associations between entities in the Knowledge Graph well, and generates a richer sequence of learning paths, which improves the accuracy of the generated learning paths. In addition, the TMLPE model also scores significantly higher than the other three models on the interpretability metric Er, which is 12.23% higher than the ELPRKG model, which is the next best performer.

Table 1: Comparison Results of learning path Recommendation Performance

Model	MRR	NDCG	Er
Clustering	0.284	0.291	0.246
ACO	0.308	0.345	0.277
ELPRKG	0.475	0.428	0.515
TMLPE	0.502	0.483	0.578

III. A. 4) Case studies

In this paper, learner A in the MOOPer dataset is randomly selected as the research object, and the case study of explainable learning path recommendation based on knowledge graph is carried out. When learner A is studying the "test" course, the learning scene is "pre-test review", the starting learning unit is "basic vocabulary and grammar", and the target learning unit is "English writing and communication ability", and learner A can get a total of 8 learning paths from S1~S8.

In this paper, we normalize scoa(pr) (learner A's acceptance score of the recommended path), scos(pr) (the fit between the recommended path and the learning scenario), scoA(pr) (the match between the recommended path and the learner), and Er (the total interpretable score of the recommended path), and the score results are shown in Table 2. Path P1 has the shortest learning duration and the highest average number of learning unit submissions, which is more in line with the path characteristics required by the “pre-test review” scenario, and therefore its scos(pr), scoA(pr), and Er scores are all the highest, reaching 0.269, 0.198, and 0.205, respectively, whereas P7 has the longest learning duration and the highest average number of learning unit submissions. learning duration is the longest, and the average number of submissions, viewers, and likes of the learning unit is the lowest, so its scoa(pr), scos(pr), and scoA(pr) scores are all the lowest, and its Er score is also the lowest. Therefore, for learner A, path P1 is the more suitable path for his learning. Based on the above analysis, the recommended results are output for the recommended learning path P1, which is S1-S5-S7, and the recommended learning duration is 65 minutes.

Table 2: Normalization processing results

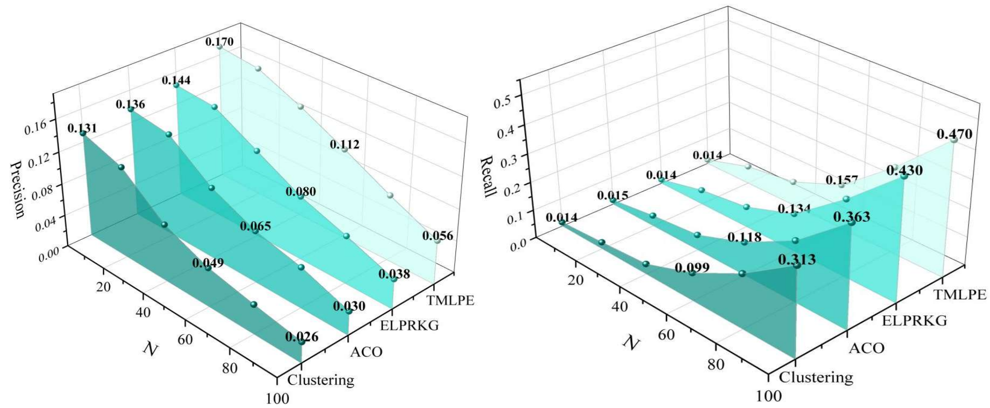
Path number	Path	scoa(pr)	scos(pr)	scoA(pr)	Er
P1	S1-S5-S7	0.192	0.269	0.198	0.205
P2	S1-S3-S4-S7	0.213	0.158	0.171	0.198
P3	S1-S5-S4-S6-S7	0.132	0.125	0.153	0.141
P4	S1-S2-S6-S7	0.141	0.135	0.142	0.147
P5	S1-S3-S5-S6-S7	0.178	0.133	0.145	0.158
P6	S1-S3-S2-S6-S7	0.102	0.122	0.125	0.114
P7	S1-S3-S4-S5-S6-S7	0.083	0.099	0.105	0.101

In order to verify the effectiveness of the model, the Clustering model, ACO model, ELPRKG model and the model of this paper are compared. The effectiveness of the algorithm is measured from the perspective of checking accuracy and recall indicators in Top-N task, and the experimental results are shown in Fig. 2(a~b). By comparing and analyzing the experimental data, it can be seen that the TMLPE model achieves the best performance in both checking accuracy and recall evaluation indexes.The Clustering model relies too much on the completeness and abundance of the data, and is prone to fall into the quagmire of data sparsity and cold start.The pheromone updating mechanism adopted by the ACO model has a weak capability of capturing the global information of the knowledge graph, and is prone to the local optimization problem. The ELPRKG model starts from the user's end and enhances the user's representation by propagating the user's latent preferences, but it does not consider the entity weights in the knowledge graph, thus not focusing the recommendation on the entities with a higher degree of importance.The TMLPE model highlights the focus of the recommendation with the help of the interaction feature capture module, and the basic feature capture module is able to more comprehensively and efficiently capture the semantic associations between the entities and the relationships, which This increases the accuracy of recommendation, thus improving the recommendation performance.

III. B. Application effects

In order to better test the personalized learning effect of the intelligent recommendation system based on the model in this paper, to figure out whether the personalized learning path recommended by the system can effectively meet the learners' differentiated learning needs and promote the achievement of the learners' learning goals, and thus ultimately promote the realization of personalized learning. This study takes English majors in University C as an example, and conducts a semester-long practical investigation on the personalized teaching mode assisted by the intelligent recommendation system, in order to better grasp the impact of the system's path recommendation on learners' personalized learning.

In this paper, we take the teaching mode as the independent variable, mainly including the traditional teaching mode and the personalized teaching mode based on the intelligent recommendation system, and observe the dependent variable of students' learning effect, which is the achievement of personalized learning goals. The subjects of the study are the students of four classes in the second year of English majors in University C, with about 40 students in each class, and the total number of samples is 160. The samples were equally divided into experimental and control groups, with the experimental group adopting the blended teaching mode of intelligent recommender system-assisted teaching and the control group adopting the traditional teaching mode. In the experiment, the arithmetic mean of the students' scores in the midterm examination of college English in each class was used as the reference quantity, and the overall level of the students in each class was similar, and the distribution of the students' level within the class was also similar. In addition, the teaching experience and style of the appointed teachers are similar, and the teaching content and progress are also the same, which can effectively exclude the interference of other irrelevant variables.



(a) Precision (b) Recall

Figure 2: Comparison of precision rate and recall rate indicators

The purpose of this paper is to gain insight into the realization of students' personalized learning needs and personalized learning goals by the intelligent recommender system based on the multilayer perceptual machine model through a questionnaire survey, and the personalized learning needs include content needs, resource needs and process needs, and the personalized learning goals include knowledge and skills, process and method, and affective attitudes. The questionnaire was scored using a five-point Likert scale, and the data were analyzed by SPSS 20.0.

III. B. 1) Comparison of learning outcomes

In order to test the difference between the effects of personalized learning in the blended teaching environment and the traditional teaching environment, this paper analyzes the differences in the achievement of personalized learning goals between the experimental group and the control group.

The t-test was used to test the differences between the two different teaching modes, hybrid and traditional, on the dimensions of the personalized learning objectives, and the results of the analysis of variance are shown in Table 3. Different modes of teaching activities showed a significant difference of 0.01 in the dimensions of learners' "knowledge and skills", "process and methods", and "emotional attitudes" ($P=0.00<0.01$), and compared with the mean values of 3.95>3.42, 4.06>3.15, 3.96>3.11, it was found that the mean value of the experimental group was greater than that of the control group. The blended teaching model based on the intelligent recommendation system can promote the personalized learning of students.

Table 3: Differential Analysis of Personalized Learning Effects

Dimension	Class	Sample size	Average value	Standard deviation	T	P
Knowledge and Skills	Experimental group	80	3.95	0.5866	0.031	0.00
	Control group	80	3.42	0.6182		
Process and Method	Experimental group	80	4.06	0.6286	0.062	0.00
	Control group	80	3.15	0.6052		
Emotional attitude	Experimental group	80	3.96	0.5937	0.047	0.00
	Control group	80	3.11	0.5836		

III. B. 2) Correlation analysis between learning needs and learning objectives

(1) Content demand dimension

The Pearson correlation coefficient is used to indicate the strength of the correlation, and the learners' content needs and personalized learning objectives are tested in the correlation analysis. First of all, the P-values of each dimension of content needs and personalized learning objectives in general, that is, the Sig values in the table, are all less than 0.01, which proves that the learners' content needs and personalized learning objectives show significance at the 0.01 level. And the R-values are all positive, indicating a positive correlation between the two. The specific correlation coefficient values of the dimensions of content needs and the dimensions of personalized learning objectives are shown in Table 4, and the R values are all in the range of 0.6 to 0.9, indicating that there is a close correlation between learning activities and personalized learning objectives.

Table 4: Correlation Analysis of Content Requirements and Learning Objectives

Dimension		Knowledge and Skills		Process and Method		Emotional attitude	
		R	Sig. (Bilateral)	R	Sig. (Bilateral)	R	Sig. (Bilateral)
Content requirements	Content difficulty	0.826	0.000	0.704	0.007	0.897	0.000
	Content breadth	0.738	0.001	00.683	0.005	0.882	0.001
	Learning activities	0.875	0.000	0.721	0.000	0.795	0.000

The blended teaching mode based on the intelligent recommendation system can set and push the teaching content as well as learning tasks and assignments suitable for different levels of students according to their level bases, which is conducive to improving learners' self-efficacy, full of confidence in learning, and generating a stronger interest in learning by completing the learning tasks suitable for their level. Especially in a language subject like English, increased self-efficacy helps students to express themselves bravely and improve their ability to express themselves and do things in English. Moreover, personalized learning paths allow learners to choose a variety of learning contents according to their own preferences and levels to a certain extent, which greatly enhances students' interest in learning, and then promotes the change of their learning attitudes, the enhancement of their intrinsic motivation, and the improvement of their will to learn.

(2) Resource Demand

The correlation analysis between learners' resource needs and personalized learning objectives is conducted, and the results of Pearson correlation coefficient test are shown in Table 5. First of all, the P-value (Sig value) of the correlation between the dimensions of resource type, amount of resources, and learning partners under the dimension of learners' resource needs and personalized learning goals is <0.05, which proves that the learners' resource needs and personalized learning goals show significance at the 0.05 level. And the R-values are all positive, indicating a significant positive correlation between the two. The correlation coefficients of the dimensions of resource type, resource amount, and learning partners with the dimensions of personalized learning goals are 0.5 < R value < 0.8, which indicates that there is a closer influence between resource needs, including resource type, resource amount, and learning partners, and personalized learning goals.

Table 5: Correlation Analysis of Resource Requirements and Learning Objectives

Dimension		Knowledge and Skills		Process and Method		Emotional attitude	
		R	Sig. (Bilateral)	R	Sig. (Bilateral)	R	Sig. (Bilateral)
Resource requirements	Resource type	0.686	0.009	0.583	0.000	0.735	0.000
	Resource quantity	0.773	0.002	0.799	0.023	0.744	0.012
	Learning partner	0.697	0.000	0.685	0.018	0.656	0.000

Through data analysis, it is found that the blended teaching mode based on the intelligent recommendation system can well meet the learners' needs for personalized learning resources in terms of resource type, resource amount and learning partners. In this teaching mode, teachers will provide learners with resources suitable for different students and adapt to their learning needs.

(3) Process needs

The correlation analysis between the dimensions of learners' process needs in learning and personalized learning goals shows that there is a high correlation between the satisfaction of learners' process needs and the achievement of personalized learning goals, and the specific results are shown in Table 6. First of all, the P-value (Sig value) of learning mode, learning progress, interaction mode and interaction frequency dimensions under the dimension of learners' process needs and the dimensions of personalized learning goals = 0.000<0.01, which proves that the process needs of learners and the personalized learning goals show significance at the 0.01 level. And the correlation coefficients R values are all positive, indicating a significant positive correlation between the two. The correlation coefficients of R value of each dimension of learning mode, learning progress, interaction mode and interaction frequency with the dimensions of personalized learning objectives are all greater than 0.7, which indicates that there is a close influence between the process needs and personalized learning objectives, and in particular, there is a high correlation between the learners' affective attitudes, with the R values of more than 0.9.

Table 6: Correlation Analysis of Process Requirements and Learning Objectives

Dimension		Knowledge and Skills		Process and Method		Emotional attitude	
		R	Sig. (Bilateral)	R	Sig. (Bilateral)	R	Sig. (Bilateral)
Process requirements	Learning method	0.822	0.000	0.817	0.000	0.903	0.000
	Learning progress	0.709	0.000	0.732	0.000	0.918	0.000
	Interaction mode	0.864	0.000	0.803	0.000	0.906	0.000
	Interaction frequency	0.773	0.000	0.726	0.000	0.915	0.000

Through data analysis, it is found that the blended teaching mode can well meet the needs of learners for personalized learning process in terms of learning mode, learning progress, interaction mode and interaction frequency. Students can conduct independent inquiry learning based on the resources pushed by the teacher, which promotes the formation of “personalized knowledge”. Learners also have greater autonomy over the learning time and learning progress, and they can make full use of the knowledge map to better master the learning method. Under the blended teaching environment, teachers also pay more attention to the cultivation of students' learning styles, guiding them to learn independently, cooperatively and through inquiry.

IV. Conclusion

In this paper, an intelligent recommendation system based on multilayer perceptual machine model is designed to explore the effectiveness of TMLPE model and the practical application effect of the intelligent recommendation system by setting up experiments.

The scores of TMLPE model on MRR and NDCG indicators are 0.502 and 0.483 respectively, which are higher than the baseline model. The score on the interpretability indicator Er is also significantly higher than the other three models, and is 12.23% higher than the ELPRKG model, which has the second best performance. In the case study, the TMLPE model showed the best performance on both the check accuracy and recall assessment metrics.

In the teaching experiment with the teaching model as the independent variable, the teaching activities of different models show significant differences in the dimensions of learners' “knowledge and skills”, “process and method”, and “affective attitude” at the 0.01 level. There is a significant difference at the 0.01 level (p=0.00<0.01), and the mean values of the experimental group are larger than those of the control group, with the mean values comparing 3.95>3.42, 4.06>3.15, 3.96>3.11. The p-values of the dimensions of the content needs and the personalized learning objectives in general are all less than 0.01, and the R-values are in the range of 0.6 to 0.9. The P-value of correlation with personalized learning objectives under the dimension of resource demand is less than 0.05, and the correlation coefficient is 0.5<R-value<0.8. The P-value of each dimension of process demand with each dimension of personalized learning objectives=0.000<0.01, and the R-values are all greater than 0.7, in which the aspects of emotional attitudes towards learners show high correlation, and the R-values are all in the range of 0.9 or more.

Teachers supported by the intelligent recommender system in the blended environment can better provide personalized learning services for students, so that the learning path selection is more in line with the learning needs of individuals, which leads to a positive shift in the mastery of learning methods, improvement of reflective ability, learning process experience and affective attitudes of students.

References

[1] Gudoniene, D., Staneviciene, E., Huet, I., Dickel, J., Dieng, D., Degroote, J., ... & Casanova, D. (2025). Hybrid Teaching and Learning in Higher Education: A Systematic Literature Review. Sustainability, 17(2), 756.

[2] Bekmuradovich, S. A. (2025). The usage of modern educational technologies in teaching a foreign language in higher educational institutions. Ta'lim, tarbiya va innovatsiyalar jurnali, 1(2), 180-184.

[3] Song, Y. (2017, May). Reform and Development of College English Education. In 2017 4th International Conference on Education, Management and Computing Technology (ICEMCT 2017) (pp. 157-161). Atlantis Press.

[4] Xu, J., & Fan, Y. (2017). The evolution of the college English curriculum in China (1985–2015): Changes, trends and conflicts. Language Policy, 16, 267-289.

[5] Kaya, E. A., & Avara, H. (2025). Education Informatics Network-Based Blended Learning in High School English as a Foreign Language Context. Journal of Learning and Teaching in Digital Age, 10(1), 44-57.

[6] Seitova, M., & Khalmatova, Z. (2025). THE BLENDED LEARNING STATION ROTATION MODEL IN EFL TEACHING: OPINIONS OF THE IMPLEMENTER. Turkish Online Journal of Distance Education, 26(1), 204-219.

[7] Du, C., & Yang, Y. (2025). Exploring EFL learners' need satisfaction, need frustration, and their motivational change in a blended English learning environment. International Journal of Applied Linguistics, 35(1), 400-419.

[8] Bensalem, E., Derakhshan, A., Alenazi, F. H., Thompson, A. S., & Harizi, R. (2025). Modeling the contribution of grit, enjoyment, and boredom to predict English as a foreign language students' willingness to communicate in a blended learning environment. Perceptual and Motor Skills, 132(1), 144-168.

[9] Luo, L. (2025, March). Fostering Higher-Order Thinking Skills of Undergraduate Students: The Integration of Blended Learning in College English Teaching. In 2025 14th International Conference on Educational and Information Technology (ICEIT) (pp. 281-290). IEEE.

[10] Li, M., & Yu, Z. (2025). Critical Success Factors Influencing English Learning Outcomes in Blended Learning Environments. SAGE Open, 15(1), 21582440251320052.

[11] Boymuartovna, A. Z. (2025). BLENDED LEARNING STRATEGIES IN TEACHING ENGLISH GRAMMAR TO NON-NATIVE SPEAKERS. THE THEORY OF RECENT SCIENTIFIC RESEARCH IN THE FIELD OF PEDAGOGY, 3(32), 113-117.

[12] Liu, L. (2025). Research on the Blended Teaching Model of Translation Courses for English Majors in the Context of New Liberal Arts. Evaluation of Educational Research, 2(7).

[13] Xue, C. (2025). A Study on Blended Teaching Model Evaluation for English Major Courses in Higher Education: An Uncertainty-Based Approach. Neutrosophic Sets and Systems, 80(1), 30.

[14] Feng, G. (2024). Blended Teaching Mode Model of College English Based on Collaborative Filtering Recommendation Algorithm. J. Electrical Systems, 20(6s), 247-253.

[15] Guo, Z. (2023). An empirical analysis on the cultivation of English innovative application ability of English majors in application-oriented universities based on dynamic optimization algorithm in blended teaching environment. Soft Computing, 27(15), 10839-10850.

[16] Yuanda, G. (2024). Application of wireless sensor network based on improved genetic algorithm in English blended learning. Measurement: Sensors, 33, 101174.