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Exploring the Application of Artificial Intelligence Technological Innovation in the Reform of Teaching Methods for Teachers of Higher Vocational Marketing Majors

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Abstract With the continuous exploration of AI application fields, the application of "AI+Education" in the higher education market is also deepened. The article studies the personalized recommendation learning method based on deep knowledge tracking. The method adopts a dynamic key-value memory network that integrates the attention mechanism, and extracts and stores the features between students and marketing training exercises. Students' dynamically changing marketing competency levels are tracked by a bidirectional gated recurrent unit neural network. The method of two exercises filtering is designed to calculate the cognitive similarity, the similarity of the difficulty of the exercises and the difficulty of the exercises of the students to achieve the recommendation of personalized exercises for senior marketing majors. The accuracy, novelty and diversity of the recommended exercises of this paper's method are improved compared with the comparison model, and its recommendation accuracy is improved by 4.00% on the ASSISTment2009 dataset compared with the sub-optimal model. The posttest scores of the experimental class based on this paper's personalized recommendation learning method gained significant improvement compared with the pre-test, and also gained significant improvement compared with the posttest scores of the control class. It shows that the method of this paper can provide reliable learning resources recommendation for senior marketing students and is suitable for personalized teaching by senior marketing teachers.

Index Terms Attention mechanism, Dynamic key-value memory network, Bidirectional gated recurrent unit neural network, Personalized exercise recommendation

I. Introduction

As a market-oriented profession, marketing is always in the wave of continuous change, a series of new ideas, new methods and new technologies continue to emerge, bringing new opportunities and challenges for the senior marketing profession. In order to continue to promote the digital empowerment of higher vocational marketing professional teaching quality improvement, it is required to build a new type of teaching mode under the background of digitalization to help improve teaching efficiency and quality [1], [2]. Therefore, how to effectively integrate information technology and marketing teaching has become a major problem in the current high-quality development of higher vocational institutions [3]. The adaptation of students to the emerging education methods, the improvement of teachers' digital literacy ability, and the investment in the application of information technology construction in higher vocational colleges and universities have become the key factors affecting the effectiveness of marketing teaching reform in higher vocational colleges and universities [4]-[6].

In recent years, with the rapid development of artificial intelligence, the field of marketing personnel training has gradually become one of the important application fields of artificial intelligence [7]. Using artificial intelligence to conduct market research, teachers can obtain a large amount of valuable market data in a short period of time, which allows teachers to quickly understand market dynamics, grasp consumer demand, and provide a basis for the development of course content [8]-[10]. In addition, teachers can use artificial intelligence tools to analyze the collected market data in depth, discover the patterns and trends behind the data, and help students better understand marketing strategies and techniques [11]-[13]. Based on this, higher vocational colleges and universities should actively explore and innovate the application of artificial intelligence to continuously improve the quality of teaching and the employment competitiveness of students, and make positive contributions to the development of the marketing field [14], [15].

In this paper, we first discuss the innovative application strategy of artificial intelligence technology in the teaching of teachers of senior marketing majors, and design a method to track students' knowledge level based on dynamic key-value memory network. The interaction features between students and exercises are mined and stored, and then the laws of students' knowledge level over time are captured by Bi-GRU model to predict the probability of students completing the questions correctly. The students are then initially screened by the knowledge mastery matrix, and the second screening is performed by the students' cognitive state and the difficulty of the test questions to generate the personalized exercise sets to be recommended. The performance of this paper's method is verified by comparing three different datasets, and students majoring in marketing in X school are selected as the research object to test the usability of this paper's method in teaching practice through the change of students' pre- and post-test scores.

II. Innovative applications of artificial intelligence technologies in teaching methods

II. A.Framework of blended teaching model for marketing majors

To build an AI-enabled blended teaching framework centered on course teaching, to form a blended teaching framework with the key points of pre-course exploration, classroom learning, post-course assessment and comprehensive evaluation, to combine AI and blended teaching in the course process, and to utilize AI's data statistics, machine learning and intelligent recognition functions to realize online resource sharing, offline real-time interaction, online instant Q&A, and online and offline comprehensive assessment of the blended teaching respectively. Offline comprehensive evaluation, to provide rich and comprehensive learning resources for pre-course independent exploration, timely supervision of classroom learning effects, to ensure post-course self and online assessment, and through the classroom students' emotions, micro-expression management and other artificial intelligence intelligent classroom management, the formation of students' objective learning initiative evaluation, and ultimately for the comprehensive evaluation of the comprehensive evaluation of the evaluation of the data to bring objective and comprehensive evaluation data, so as to effectively supervise the implementation of the teaching method to ensure the continuous improvement of the quality of teaching. The quality of teaching is guaranteed to be continuously improved.

Constructing a multidimensional evaluation system for blended teaching under artificial intelligence using artificial intelligence to enhance the blended teaching process and summative multidimensional evaluation system, analyzing and counting big data such as facial expressions, body postures, and brain waves through artificial intelligence recognition technology based on machine learning and deep learning, forming an objective evaluation of the students' learning process, and combining the evaluations of the students, parents, and teachers, to set up a more three-dimensional and multidimensional Evaluation system to provide a strong guarantee for the implementation and execution of blended teaching.

Carrying out the practice of blended teaching of marketing majors under artificial intelligence is based on the preliminary theoretical conception, using artificial intelligence technology to carry out practical application in blended teaching of marketing majors, using practice to perfect and improve the theory, and improving the quality of teaching and enhancing the professional quality of students through practice.

II. B.Blended online and offline teaching and learning implementation

During the implementation of online and offline blended teaching, it is important to focus on pre-course preparation, classroom interaction and post-course assignments in order to achieve the best teaching results.

Pre-course preparation. Pre-course preparation is the first step in the implementation of blended teaching. Teachers need to prepare online teaching resources in advance, such as videos, courseware, cases, etc., and release them to the teaching platform. At the same time, students need to do pre-course study, understand the relevant knowledge and background information, and prepare for classroom learning. Take Marketing as an example, the teacher will send the teaching courseware to the platform and let students study the first chapter and the second chapter online and complete the chapter test, and then leave the homework. For example, briefly describe the evolution of marketing philosophy, briefly describe the process of planning the implementation of marketing strategy, how to understand “the purpose of marketing is to make sales redundant”.

Classroom interaction. Classroom interaction is a key link in the implementation of blended teaching. In classroom teaching, teachers should make full use of online and offline teaching resources to guide students to actively participate in discussion, cooperative learning and problem solving activities. At the same time, teachers should pay attention to the individual differences and needs of students and give targeted guidance and support. Still taking Marketing as an example, class discussion on the homework left before class.

After-class homework. After-class homework is an important means of consolidating classroom knowledge and improving students' learning ability. When assigning after-class homework, teachers should consider the actual situation and learning needs of students and design homework topics with practical significance. At the same time, teachers should pay attention to the completion of students and give timely feedback and guidance. For example, do a marketing planning program or do a market research project.

Students' self-initiated learning. Students can complete their learning on the teaching platform, through online teaching for literature reference, discussion and exchange, and interactive Q&A of the teacher team. For example, students can look for relevant literature according to the teacher's lesson plan and the reserved homework, and they can also communicate and discuss with their classmates, and even ask questions online to the teacher about some of the knowledge they don't understand. This not only improves students' learning efficiency, but also stimulates their interest in independent learning.

III. Personalized recommended teaching methods based on deep knowledge tracking

III. A. General

The deep knowledge tracking personalized recommendation learning method proposed in this paper firstly uses dynamic key-value memory network (DKVMN) [16] to extract and store the characteristics of historical learning task interactions between the students and the marketing practical training topics, and to mine the correlation between the course knowledge points and the marketing topics; and then through the bi-directional gated recurrent unit (Bi-GRU) model to bi-directionally track the changes in the marketing level of the students over time, to And then predict the probability of correctly completing the topic to improve the accuracy and interpretability of the recommendation results; finally, based on the recommendation degree of the topic, generate a personalized recommendation scheme and present it visually.

The method is divided into four levels as follows.

(1) Embedding layer. Pre-processing the log information of the practical training situation of student s, embedding all the historical practical training records of s before the moment of t into a high-dimensional vector space after One-Hot encoding to form a continuous embedding vector.

(2) Internal storage layer. Contains attention, read and write mechanisms for correlating the knowledge points stored in M^k with the mastery level of the knowledge points stored in M^v, and updating the current mastery level of the knowledge points of the student s by calculating the knowledge point composition and the knowledge state vector in the marketing topic.

(3) Knowledge tracking layer. Bi-directional modeling of students' marketing competency level status by using the Bi-GRU model to track and extract the characteristics of students' historical competency level sequence at t moment.

(4) Output layer. Based on the prediction of the probability of students answering the exercise correctly at the $t+1$ moment, the topic recommendation degree is calculated by combining the set of learning attributes of students, and the personalized recommendation scheme is finally generated.

III. B. Key-Value Memory Correlation Mechanisms

In DKVMN, the key-value pair structure is utilized to record the interaction information between students and the marketing practical training topics, in which the static key matrix M^k is used to store the individual knowledge points associated with the topics, with the size of $N \times d_k$; and the dynamic value matrix M^v is used to store and update the students' mastery of the course knowledge points, with the size of is $N \times d_v$. where N is the number of memory slots, and both d_k and d_v are the sizes of the vectors stored in the respective memory slots. The values in M^v are continuously updated during the learning process based on the progress of the students' practical marketing training.

III. B. 1) Attention mechanisms

The attention mechanism [17] is mainly used to compute the weight matrix w_t. In this mechanism, the topic q_t is taken as input and q_t has been vectorized into a One-Hot vector.

In order to map q_t to the internal storage layer, it needs to be multiplied with the embedding matrix A to generate the continuous embedding vector k_t. k_t contains information about the students' marketing practical training interactions, including the number of practice sessions, practice behaviors, and the results of quantitative evaluation of learning ability. Make an inner product of k_t and each column in M^k, and then apply the activation function Softmax in the fully connected layer to obtain the attention weight vector $w_t(i)$. $w_t(i)$ denotes the correlation between q_t and the topic-associated knowledge points stored in M^k, and $i \in (1, N)$ is the course knowledge point ordinal number, which is calculated as follows:

$$w_t(i) = Softmax(k_t^T M^k(i)) \tag{1}$$

where $Softmax(z_i) = e_i^z / \sum_j e_j^z$, which is an activation function. z_i is the independent variable of the function, which is used to refer to $k_t^T M^k(i)$ in Eq. (1); e is the base of the natural logarithm.

III. B. 2) Reading mechanism

The read mechanism is used to characterize the change in the students' level of mastery of marketing knowledge points. According to the corresponding attention weight vector w_t of the marketing practical training record information, the knowledge point mastery level of students s related to the topic q_t can be read from the value matrix M_t^v , and the read vector r_t is calculated. r_t represents the level of mastery of the knowledge points associated with q_t by s when using q_t for marketing training, and is calculated as follows:

$$r_t = \sum_{i=1}^{N} w_t(i) M_t^v(i) \tag{2}$$

Inputting r_t together with the embedding vector k_t into the activation function Tanh in the fully connected layer yields a joint vector f_t that contains the students' level of marketing competence and prior information about the topic:

$$f_t = Tanh(W_1^T [r_t, k_t] + b_1) \tag{3}$$

where $\mathrm{Tanh}(z_i) = \frac{e^{z_i} - e^{-z_i}}{e^{z_i} + e^{-z_i}}$, W_i is the weight matrix of the fully connected layer and b_1 is the bias vector. Since f_t has added the prior information of the question (such as question type, difficulty, importance of each knowledge point in q_t , etc.) to the knowledge point mastery level originally represented by r_t, then f_t can indicate the degree of mastery of q_t before s before solving q_t .

III. B. 3) Write mechanism

Based on the marketing practical training conducted by students s, DKVMN utilizes the writing mechanism to update the knowledge point mastery state in the value matrix M_t^v at the moment t to M_{t+1}^v at the moment $t+1$. This updating process can model the degree of knowledge point mastery that students forget or enhance during the marketing practical training process by first erasing the outdated knowledge point learning mastery state and then writing the new knowledge point mastery state.

In order to more accurately track changes in students' learning states, the marketing competency level f_t of students s before attempting to complete the marketing question q_t should be taken into account, as well as the corresponding standardized answer code outputs y_t for q_t . Embedding $\langle y_t, f_t \rangle$ into an embedding matrix B yields a vector of descriptions of s's knowledge growth after completing q_t v_t, also known as a write vector.

The erasure vector $e_t \in (0,1)$ is calculated based on the student answer vector v_t. e_t will be used to erase outdated knowledge point mastery states in M_t^v :

$$e_t = Sigmoid(E^T v_t + b_c) \tag{4}$$

where $Sigmoid(z_i) = l/(l + e^{-z_i})$, E^T is a relocation matrix, and b_c is the bias vector.

Based on e_τ and the weight matrix w_t , the matrix of values after erasing the obsolete knowledge mastery state at the moment of $t+1$ can be obtained $\tilde{M}_{t+1}^v(i)$

$$\tilde{M}_{t+l}^v(i) = M_t^v(i)[I - w_t(i)e_t] \tag{5}$$

where I denotes a row vector whose components are all l.

After erasure, the knowledge increment is then calculated based on the current students s practical marketing training and their mastery of the knowledge points, denoted as the update vector a_t . a_t can be found with the activation function Tanh:

$$a_t = \mathrm{Tanh}(D^T v_t + b_a)^T \tag{6}$$

where D^T and b_a are the migration matrix and bias vector, respectively. At the $t+1$ moment, the update $M_{t+1}^{v}(i)$ is calculated as:

$$M_{t+l}^{v}(i) = \tilde{M}_{t}^{v}(i) + w_t(i)a_t \tag{7}$$

At this point, the calculated $M_{t+1}^{v}(i)$ is the state of knowledge mastery of the student s after completing the marketing practical training topic q_t.

III. C. Bi-GRU-based tracking of students' marketing competencies

In order to be able to track and predict students' doing more accurately, this paper selects the bidirectional gated recurrent unit neural network (Bi-GRU) [18] to model the students' doing process in both directions, and then to track the level of students' marketing competence in the marketing practical training process. Bi-GRU can model marketing training sequence data with temporal characteristics in two opposite directions, i.e., it can extract features from students' historical marketing training interactions in both the forward and backward directions, and its network structure is shown in Figure 1.

The input to the Bi-GRU model is an interactive sequence of marketing practical training situations $X = \{x_1, x_2, \cdots, x_4\}$ for a particular student s, where $x_t = \langle y_t, f_t \rangle$ denotes the s marketing practical training when the mastery of course knowledge points (i.e. marketing competency level) is f_t, and y_t is the standard answer code output.

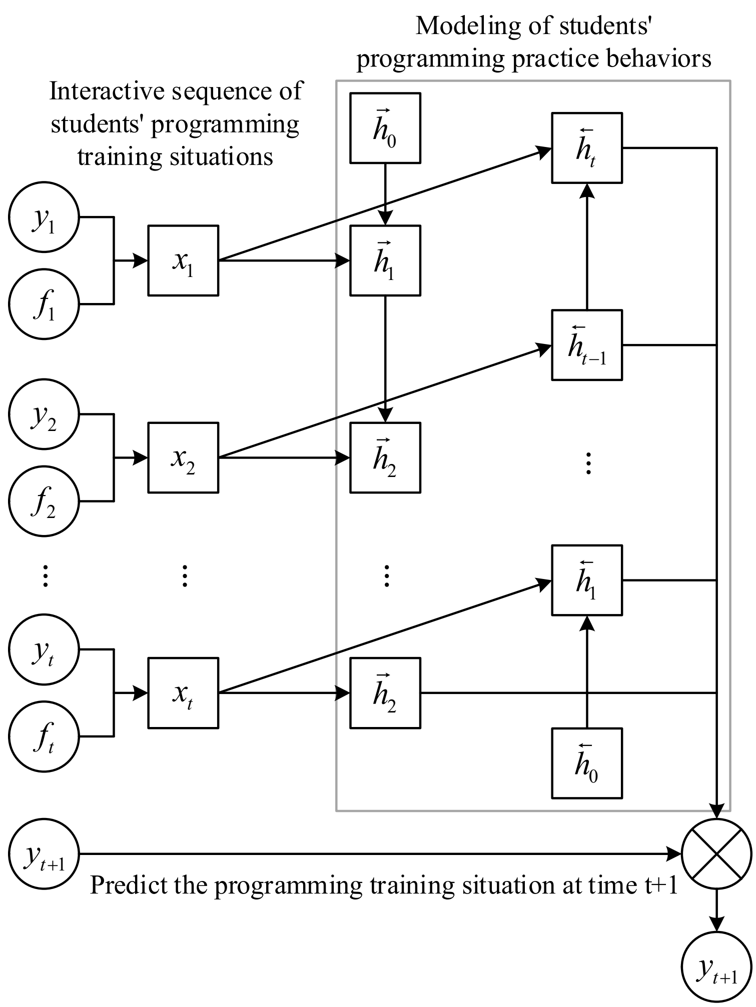

Figure 1: Student programming ability tracking model based on Bi-GRU

In the process of modeling students' marketing training behaviors, the marketing training situation interaction sequence X is used as the input, and the GRU neural network is trained simultaneously in both directions, and then the two hidden layers with opposite directions are connected to the same output, so that the output layer can obtain both forward and backward hidden state information. The hidden vector update formula can be expressed as:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{8}$$

$$c_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{9}$$

$$\tilde{h} = \tanh(W_{\tilde{h}} \cdot [r_t * h_{t-1}, x_t]) \tag{10}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{11}$$

Assuming that $\vec{h}_t \in \mathbb{R}^{n \times h}$ denotes the time-step forward hiding state, and $\tilde{h}_t \in \mathbb{R}^{n \times h}$ is the reverse hiding state , and the number of forward and reverse hidden cells is the same:

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{12}$$

$$p_t = \sigma(W_0 \cdot h_t) * y_{t+1} \tag{13}$$

III. D. SKT-MFER Exercise Recommendation Algorithm

In this paper, we obtain students' knowledge mastery through the knowledge tracking model, and find students with similar knowledge states based on these data, and then personalized exercise recommendation based on these similar students. In order to improve the recommendation accuracy, the model comprehensively considers the characteristics of students' cognitive state and the difficulty characteristics of exercises, and finally forms a multi-featured exercise recommendation model based on students' knowledge tracking (SKT-MFER), which not only accurately reflects the current cognitive level of the students, but also provides exercises with appropriate difficulty to effectively improve the learning effect of the marketing students.

III. D. 1) Initial screening based on improved similarity algorithm

The similarity calculation in the initial screening stage is improved based on the Pearson correlation coefficient. For the students to be recommended, it is more meaningful for the target students to increase the attention of the target students who have not done the questions, so that they can carry out the learning of new content and improve their knowledge mastery, so this algorithm adds the cutting factor based on Pearson's correlation coefficient, and its purpose is to cut down the weight of the questions that the target students have often done, and to improve the weight of the questions that the students to be recommended haven't dealt with. The formula for calculating the reduction factor is as follows.

$$R(q) = e^{\frac{n_q}{n}} \tag{14}$$

where q is the exercises, n is the total number of questions, n_q is the number of done questions, the larger n is, the smaller the value of $R(q)$ is, i.e., the smaller the influence of the done questions on the calculation of similarity, and accordingly the weight of the undone questions is increased, so that the probability of the target student's undone questions in the to-be-recommended question pool is increased.

Combining the above two formulas and incorporating the cut factor into the Pearson correlation coefficient, the improved similarity calculation formula is:

$$\sin(s, s') = \frac{\sum_{k \in K_{s,s'}} (a_{s,k} - \dot{a}_s)(a_{s',k} - \dot{a}_{s'}) e^{\frac{n_q}{n}}}{\sqrt{\sum_{k \in K_{s,s'}} (a_{s,k} - \dot{a}_s)^2} \sqrt{\sum_{k \in K_{s,s'}} (a_{s',k} - \dot{a}_{s'})^2}} \tag{15}$$

Among them, (s, s') are the data of the target students and similar students, $K_{s,s'}$ are the data of the overlapping knowledge points of similar students of the target students, and $a_{s,k}$ and $a'_{s,k}$ are the mastery of the knowledge points k by students s and students s', respectively. $\dot{a}_s$ and $\dot{a}_{s'}$ are the average mastery of knowledge points by student s and student s', respectively.

After the similarity calculation formula [19] is used, the most similar students of the target students can be found, and the exercise set $G(k)$ of the first stage can be combined according to the exercises in the knowledge mastery matrix of similar students.

III. D. 2) Refiltering based on cognitive state and test question difficulty

After the initial screening, in order to further optimize the recommendation algorithm, it is necessary to consider not only the characteristics of similar students' cognitive states, but also the similarity of exercises and the similarity of difficulty to make the final recommendation.

(1) Student cognitive state similarity

The cognitive state matrix and the topic cognitive attribute relationship matrix are similarity calculated to obtain the cognitive state similarity:

$$w_k = \sin(\vec{K}_i, \vec{L}_i) = \frac{\vec{K}_i \cdot \vec{L}_i}{|\vec{K}_i||\vec{L}_i|} \tag{16}$$

where $\vec{K}_i$ is the pinched cosine of the cognitive attribute vectors in the exercise library, and $\vec{L}_i$ is the pinched cosine of the cognitive state vector.

By combining the matrix of students' cognitive states and the matrix of cognitive attributes of knowledge points, it is possible to filter the test questions corresponding to knowledge points with deficient cognitive attributes.

(2) Difficulty similarity of test questions

Difficulty is a measure of test questions, each person cognitive standards are not the same, the need to set the difficulty of the test question standard is also different, so through the initial screening of the test question set and the students themselves to do the question record of the difficulty of the similarity comparison, if screened out of the difficulty of the high, on behalf of the students need to be more difficult to recommend the question, and vice versa for its recommendation of the simple questions, need to screen out the difficulty of the questions suitable for the students. That is:

$$sim(d,d') = \frac{\sum_{q \in Q_{g,g'}} (d_{g,q} - \dot{d}_g)(d_{g',q} - \dot{d}_{g'})}{\sqrt{\sum_{q \in Q_{g,g'}} (d_{g,q} - d_g)^2} \sqrt{\sum_{q \in Q_{g,g'}} (d_{g',q} - d_{g'})^2}} \tag{17}$$

where d and d' are the difficulty of the questions in the student's own record of questions taken in conjunction with the student's ability and the difficulty of the questions in the test after the initial screening, g and g' are the question bank in the record of questions in the record of learning and the set of questions in the test formed after the initial screening, and $d_{g,q}$ and $d_{g',q}$ are the difficulty of the questions corresponding to the question pool in the learning record and the difficulty of the questions corresponding to the question pool after the initial screening, $\dot{d}_g$ and $d_{g'}$ represent the average difficulty of the test questions in the two pools, respectively.

Considering that some students may not have a study record to form a test set through the initial screening, then recommendations can be made based on the difficulty of the questions in the question bank, which is categorized into three levels of difficulty, namely, easy, medium, and hard. Finally, a comprehensive similarity is calculated by joint consideration of two similarities about the test questions, which enables more accurate test question recommendation by combining multiple similarities about the test questions.

(3) Comprehensive similarity calculation

In order to combine the similarity of students' cognitive state and the similarity of the difficulty of the test questions, so as to determine a final similarity calculation result, here it is necessary to add two weighting parameters $\lambda_1, \lambda_2 \in [0,1]$, and $\lambda_1 + \lambda_2 = 1$, according to the actual situation in the test questions, real-time adjustment of the weights of the two similarity, where λ_1 belongs to the weight of the similarity of the cognitive state of the students,

λ_2 belongs to the similarity of the difficulty of the test questions weights, and the value of which can affect the similarity of the final test questions, so the value of it is very important, and its calculation formula is as follows:

$$\lambda_1 = \frac{{w_k}^2}{\sin^2(d,d') + {w_k}^2} \tag{18}$$

$$\lambda_2 = \frac{\sin^2(d,d')}{\sin^2(d,d') + {w_k}^2} \tag{19}$$

Once the weights are calculated the composite similarity is calculated with the following formula:

$$\sin(q,q') = \lambda_1 \times w_k + \lambda_2 \times \sin(d,d') \tag{20}$$

where q and q' are the set of test questions after initial screening and the set of test questions in the students' doing records, respectively.

Finally, the corresponding recommendation list is generated based on the calculation results of the comprehensive similarity, and it is recommended in order, i.e., the TopN recommendation of the exercises.

IV. Recommended results of exercises in marketing

In order to validate the effectiveness of this paper's proposed model in this paper, this section will launch a series of extensive experimental studies and provide a comprehensive comparison of different baseline algorithms with the help of three publicly available datasets.

IV. A. Data sets

The experiments in this paper are carried out based on three classic exercise recommendation datasets.

ASSISTment 2009: this dataset is a publicly available standard dataset in the field of knowledge tracking and comes from the ASSISTments online education platform.

Statics 2011: this dataset is from a university course on engineering statics and contains 189,297 interaction records, 333 students and 1,223 exercise labels.

ASSISTment 2015: this dataset is from the ASSIST-ments online education platform and contains 683,801 valid exercise records from 19,170 students and 100 knowledge points.

IV. B. Contrasting models

The comparison models used in this paper are as follows:

(1) SB-CF model: construct a student-student similarity matrix based on the exercise answer records, from which the Top10 students answering similar questions to the target students are identified, and the exercises with the difficulty label value closest to the desired difficulty are identified from the exercises answered by each of the similar students and added to the recommendation list.

(2) The SKS-CFA-ER model tracks student status on multiple concepts and contains a static matrix that stores information about knowledge points and a dynamic matrix that stores mastery levels of knowledge points.

(3) The SASRec model integrates the effects of forgetting and learning behaviors on knowledge tracking and can more accurately provide students with appropriate exercises.

(4) The KCP-ER model uses the most popular DKT method to capture students' mastery states of different knowledge, and then uses a simulated annealing algorithm to maximize the diversity of concepts in the exercise list.

IV. C. Evaluation indicators

The level of difficulty of the exercises affects student engagement in learning, so the level of difficulty determines the quality of the recommended list of exercises. The novelty of the recommended list is to ensure the effective advancement of exercises and knowledge concepts, and the variety is to increase students' interest in doing the exercises. The purpose of this paper is to ensure the appropriate difficulty and reasonable knowledge concepts of the recommended exercises, to enrich the variety of exercises, and to promote students' motivation to do the exercises. In practical application, students' difficulty level of recommended exercises can be measured by the correct answer rate. After setting the desired difficulty, the correct answer rate is calculated based on the percentage of students answering all recommended exercises correctly.

Since there are no difficulty labels in the original dataset, difficulty labels are added to the exercises.

$$difficulty_{q(k)} = \frac{\sum_{i=1}^{n}(correct_i \mid (q(k_i) == 1))}{\sum_{i=1}^{n} q(k_i)} \tag{21}$$

where n denotes the number of concepts in the corresponding dataset, $q(k_i)$ denotes the i th concept appearing in exercise $q(k)$, and $correct_i$ denotes the correctness of the i th concept.

(1) Accuracy rate

Accuracy rate is one of the most important metrics for evaluating the recommendation performance, which aims to recommend exercises of appropriate difficulty for each student. It is defined as:

$$Accuracy(L_{best}) = \frac{\sum_{i=1}^{N}(1-|\delta - D_{q_i(k)}|)}{|N|} \tag{22}$$

where $\delta - D_{qi}(k)$ is a simple metric for measuring the difficulty distance between the recommended list and the expectation. Then, the accuracy of each recommendation exercise can be expressed as $1-|\delta - D_{q_i(k)}|$.

(2) Novelty

Novelty is an important measure of a recommender system's ability to recommend uncommon items, aiming at recommending exercises for students who have a poor grasp of the knowledge concepts or have never appeared in the history of the exercise records. For the whole recommendation list, the function reflecting the novelty is as follows:

$$Novelty(L_{best}) = \frac{1}{N}\sum_{i=1}^{N}(1 - Jaccsim(H(q_i(k)), H(q_i^v(k)))) \tag{23}$$

where $H(q_i(k))$ denotes the set of knowledge concepts contained in the exercise $q_i(k)$ and $H(q_i^v(k))$ is used to store all the concepts that the student has answered correctly in the past interactions. The $Jaccsim(\cdot)$ is the Jaccard similarity between $H(q_i(k))$ and $H(q_i^v(k))$.

(3) Diversity

Diversity represents the variability of the recommended exercises, which can be expressed as the average similarity of all the exercises in the list of recommended exercises. Here the cosine similarity between two exercises is utilized to represent their differences, which can be expressed as:

$$d(q_i(K), q_j(K)) = 1 - \frac{q_i(K)\cdot q_j(K)}{\| q_i(K) \|\| q_j(K) \|} \tag{24}$$

where $q_i(K)$ and $q_j(K)$ denote the different exercises in the recommended list. The larger the difference $(q_i(k), q_j(k))$ in the list, the more diverse the recommended exercises are. Then the diversity of the whole list can be expressed as:

$$Diversity(L_{best}) = \frac{2 \sum_{q_i(k), q_j(k) \in I_{bev,is,j}} d(q_i(k), q_j(k))}{|N|(|N|-1)} \tag{25}$$

IV. D. Experimental results and analysis

In this section, we compare the model proposed in this paper with the four comparison models and evaluate their effectiveness on accuracy, novelty and diversity metrics. The results of the accuracy comparison experiments are shown in Table 1. The Improve column in Table 1 demonstrates the improvement rate of this paper's model relative to the suboptimal model under the corresponding metrics.

On all three datasets, the accuracy of this paper's model in recommending exercises is higher than that of the sub-optimal KCP-ER model, with an improvement of 4.00%, 1.72%, and 1.59%, respectively.KCP-ER utilizes the DKT model to implement the exercise recommendation, and compared to the DKT model, this paper's model is more comprehensive in modeling the knowledge state of the students, which not only takes into account the students' answering histories, but also introduces the memory network of the knowledge points. The model in this paper is more comprehensive in modeling students' knowledge status, not only considering students' answer history, but also introducing the memory network of knowledge points. Therefore, the model in this paper accurately captures students' mastery of different knowledge points and dynamically updates the knowledge state according to students' answers, thus obtaining more accurate exercise recommendation results.

Table 1: Accurate comparison of experimental results

Model	ASSISTment2009	Statics2011	ASSISTment2015
SB-CF	0.709	0.822	0.556
SASRec	0.830	0.855	0.754
KCP-ER	0.850	0.872	0.757
SKS-CFA-ER	0.804	0.815	0.723
This model	0.884	0.887	0.769
Improvement	4.00%	1.72%	1.59%

Table 2 shows the comparison of the novelty metrics of different models on the three datasets. This paper's model has the best performance, and its Novelt improves by 13.74% over the next best model SKS-CFA-ER, which is due to the fact that the average number of interactions of ASSISTments is relatively low compared to the Statistics 2011 dataset, and the probability of students to do the new question types is higher. At the same time, when students have a low level of mastery of a particular knowledge point or it has never appeared in their history, the model in this paper will be more inclined to recommend exercises that involve these knowledge points, thus increasing the novelty of the recommended exercises.

Table 2: Comparison of Novelty

Model	ASSISTment2009	Statics2011	ASSISTment2015
SB-CF	0.758	0.761	0.616
SASRec	0.783	0.884	0.687
KCP-ER	0.791	0.902	0.762
SKS-CFA-ER	0.816	0.874	0.764
This model	0.884	0.926	0.869
Improvement	8.33%	2.66%	13.74%

Table 3 shows the comparison of the diversity metrics of different models on the three datasets, and this paper's model performs the best in terms of diversity, and its Diversity improves by 9.85% on the Statistics 2011 dataset compared to the next best model, KCP-ER. Since the Statics 2011 dataset has the largest number of exercises and their knowledge concepts, more choices of exercises can be recommended to students according to the coverage of knowledge points, which improves the diversity of exercise recommendations.

Table 3: Comparison of Diversity

Model	ASSISTment2009	Statics2011	ASSISTment2015
SB-CF	0.601	0.723	0.322
SASRec	0.740	0.814	0.708
KCP-ER	0.755	0.853	0.677
SKS-CFA-ER	0.690	0.729	0.596
This model	0.767	0.937	0.734
Improvement	1.59%	9.85%	3.67%

In this paper, the ASSISTment2009 dataset is used as an example to visualize the performance of the algorithm, and Fig. 2 shows the accuracy performance of the generated list of recommended exercises on the dataset. Compared with the baseline model, the list of recommended exercises generated using the model in this paper shows a clear advantage in terms of accuracy, and its trend is flat, the number of recommended exercises in 100, the recommendation accuracy has reached more than 90%, with higher stability.

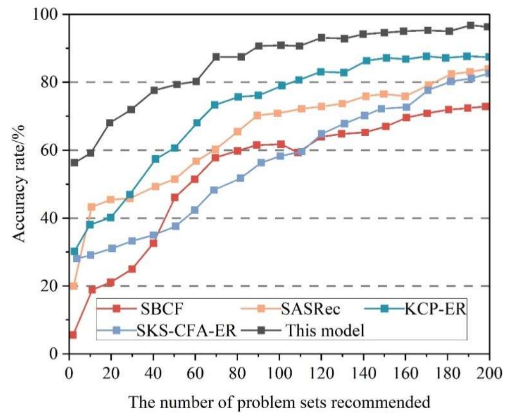

Figure 2: Specific performance of accuracy

Meanwhile, Figure 3 shows the novelty of the recommended exercise list generated on the dataset. The results show that the novelty of this paper's method fluctuates in the range of [0.6, 1.0], and the list of exercises generated using this paper's model has a higher novelty, which means that the exercises recommended by this paper's model are more innovative and more capable of meeting the needs of the students as compared to the comparative methods.

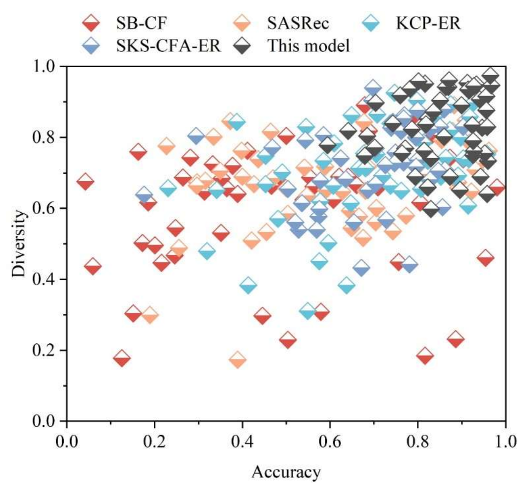

Figure 3: The novelty of the recommended problem list

Figure 4 shows the diversity performance of the generated recommended exercise lists. Obviously, the list of recommended exercises generated using the model of this paper shows obvious advantages in terms of diversity, and 50% of the diversity performance of this paper's method is gathered above 0.9, and the diversity index of this paper's model is also more stable. In summary, the model proposed in this paper has relatively better effectiveness and stability.

IV. E. Interpretability analysis

A student's learning sequence is selected to visualize the change process of his/her knowledge point mastery state and the correspondence with the real answering results of the exercises in the sequence, in order to show the interpretability between the knowledge point state and the answering results of the exercises, Figure 5 shows the change process of the knowledge point state.

Knowledge points 1 to 10 represent market segmentation, target market selection, product positioning, marketing theory, market research, branding, customer relationship management, digital marketing, competitive analysis and marketing performance evaluation, respectively. The squares of the heat map represent the knowledge point states, which are the probabilities predicted by the model for learners to answer the current exercise correctly. The symbols at the top represent the results of answering the exercises, with √ indicating a correct answer and × indicating an incorrect answer. Each line represents a knowledge point, from top to bottom, from knowledge point 1 to knowledge point 10. Columns indicate time, from left to right, moments 1 to 15. t = 1 moment, examining Knowledge Point 1. t

= 2 moment, students answered the exercises related to Knowledge Point 1 incorrectly, and the overall state of knowledge for Knowledge Point 1 declined.

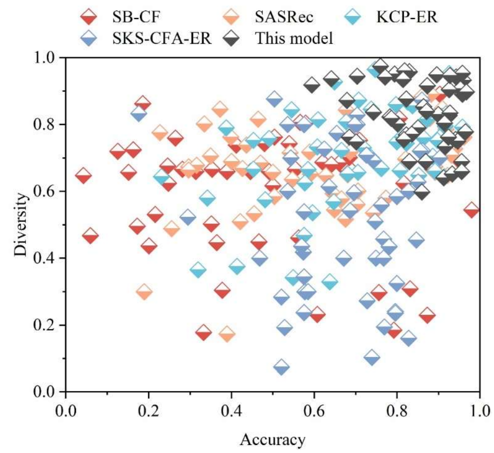

Figure 4: The diversity of the recommended problem list generated

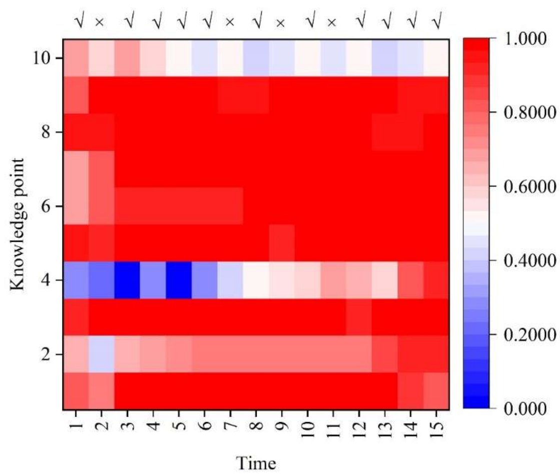

Figure 5: The process of changing the state of the knowledge

V. Analysis of the results of teaching practices

In order to understand the learning status of senior marketing students applying personalized recommendation teaching methods. The author used random sampling method to select two classes of students to participate in the survey in marketing majors in X school, the experimental class used the personalized recommendation teaching method of this paper to carry out an eight-week study, and the control class used the normal teaching method, there are 35 students in both classes.

Through the analysis and comparison of the pre and post-test scores of the experimental class and the post-test scores of the control class of the experimental class, the effect of the personalized recommendation teaching method into teaching practice is examined from the dimension of learning achievement.

V. A. Changes in pre- and post-test scores in experimental classes

In order to test the implementation effect of the personalized recommendation teaching method in this paper, and compare the changes in the pre and post-test scores of the experimental class of the personalized recommendation teaching method integrated into the course of “Customer Relationship Management”, the author used the SPSS26.0 software to carry out an independent sample t-test on the pre and post-test scores of the experimental class.

The average pre-test score of the experimental class is 62.61, and the average post-test score is 67.89, and the average post-test score is 5.28 points higher than the average pre-test score, so this paper's personalized recommendation teaching method into the “Customer Relationship Management” has a certain role in helping to improve academic performance.

Independent samples t-test is conducted on the pre and post-test scores of the experimental class, and the specific analysis results are shown in Table 4. The results show that the experimental class before and after the test scores of independent samples T-test t-value is -2.045, P-value is 0.043, less than 0.05, the results show that this paper's personalized recommendation teaching method into the teaching of the experimental class of “customer relationship management” before and after the test scores of a significant difference in this paper's personalized recommendation teaching methods into the course of the students' learning achievements have a greater impact.

Table 4: Test of independent sample t survey of experimental results

		Levin variance equivalence test		T test						
		F	Sig.	t	df	Sig.2	MD	SE	95%CI Upper limit	95%CI Lower limit
Pre	Equal.Var.	0.145	0.706	-2.045	69	0.043	-4.561	2.158	-8.845	-0.095
	Unequal.Var.			-2.045	68.451	0.043	-4.561	2.158	-8.845	-0.095

V. B. Changes in the performance of the experimental class control class after the experiment

After 8 weeks of teaching practice, the posttest scores of the experimental class control class were compared and analyzed to test the effectiveness of teaching. With the help of SPSS26.0 software, an independent sample t-test was conducted on the post-test scores of the two classes to test whether the scores of the two classes constituted a significant difference. Comparing the average scores of the two classes after the experiment, the average score of the experimental class was 67.89 and that of the control class was 62.11, and the average score of the experimental class was 5.78 points higher than that of the control class. In terms of academic achievement dimensions, the experimental class was better than the control class, and the integration of the personalized recommended teaching methods of this paper into teaching helped to improve performance.

Table 5 shows the independent sample T-test of the post-test scores of the experimental class and the control class, according to the independent sample T-test of the post-test scores of the two classes, the T-value is 2.165, and the P-value is 0.035, which is less than 0.05, indicating that there is a significant difference between the post-test scores of the two classes. After analysis, after the personalized recommendation teaching method of this paper is integrated into Customer Relationship Management, the learning achievement of the experimental class is significantly improved and significantly higher than that of the control class.

In conclusion, after eight weeks of teaching practice, the learning achievement of the experimental class in the course of “Customer Relationship Management” has been significantly improved, and the learning effect of the experimental class is significantly better than the control class after the concept of personalized recommendation teaching method of this paper is integrated into this course. This also indicates that the integration of personalized recommendation teaching method into the course of Customer Relationship Management can help students improve their professional performance.

Table 5: Test of test results of the experimental class

		Levin variance equivalence test		T test						
		F	Sig.	t	df	Sig.2	MD	SE	95%CI Upper limit	95%CI Lower limit
Pre	Equal.Var.	0.003	0.955	2.165	67	0.035	4.859	2.265	0.377	9.425
	Unequal.Var.			2.165	66.452	0.035	4.859	2.265	0.377	9.425

VI. Conclusion

In this paper, a personalized recommendation learning method based on deep knowledge tracking is investigated and applied to the teaching of practical training for senior marketing majors.

The accuracy of recommended exercises of this paper's method on three datasets, ASSISTment2009, Statics 2011 and ASSISTment2015, is improved by 4.00%, 1.72% and 1.59%, respectively, compared with the sub-optimal KCP-ER model. The novelty and diversity of the models are both improved to some extent compared to the comparison models. It shows that the DKVMN model applied in this paper is more comprehensive in tracking students' knowledge status compared to the DKT model of the KCP-ER model. Therefore, the model in this paper can obtain more accurate exercise recommendation results.

The average performance of the post-test of the experimental class with the application of this paper's personalized recommendation learning method gains 5.28 points compared with the average performance of the pre-test. The independent sample t-test t-value of the pre-test and post-test scores of the experimental class is -2.045, and the p-value is less than 0.05, which indicates that there is a significant difference between the pre-test and post-test scores of the experimental class of senior marketing majors after the personalized recommendation learning method of this paper is integrated into actual teaching. The average score of the experimental class is 5.78 points higher than that of the control class, and there is also a significant difference in the independent samples t-test of the post-test scores of the two classes. Once again, it shows that the method of this paper has a significant effect on improving the academic performance of the students in the experimental class, and it is significantly higher than that of the control class. It confirms the feasibility of the innovative teaching method of this paper in teaching practice.

References

[1] Telli, S. G., & Aydın, S. (2021). Digitalization of marketing education: new approaches for universities in the post-Covid-19 era. Üniversite Araştırmaları Dergisi, 4(1), 61-74.

[2] Crittenden, V., & Peterson, R. A. (2019). Digital disruption: The transdisciplinary future of marketing education. Journal of Marketing Education, 41(1), 3-4.

[3] Ferrell, O. C., & Ferrell, L. (2020). Technology challenges and opportunities facing marketing education. Marketing Education Review, 30(1), 3-14.

[4] Ye, C., Kim, Y., & Cho, Y. N. (2024). Digital marketing and analytics education: A systematic review. Journal of Marketing Education, 46(1), 32-44.

[5] Grewal, D., Guha, A., Beccacece Satornino, C., & Becker, M. (2025). The future of marketing and marketing education. Journal of Marketing Education, 47(1), 61-77.

[6] Rohm, A. J., Stefl, M., & Saint Clair, J. (2019). Time for a marketing curriculum overhaul: Developing a digital-first approach. Journal of Marketing Education, 41(1), 47-59.

[7] Guha, A., Grewal, D., & Atlas, S. (2024). Generative AI and marketing education: What the future holds. Journal of Marketing Education, 46(1), 6-17.

[8] Elhajjar, S., Karam, S., & Borna, S. (2021). Artificial intelligence in marketing education programs. Marketing Education Review, 31(1), 2-13.

[9] Hu, J., Liu, B., & Peng, H. (2021). Role of AI for application of marketing teaching–A research perspective. Journal of Intelligent & Fuzzy Systems, 40(2), 3711-3719.

[10] Dubay, C. M., & Richards, M. B. (2024). Leveraging artificial intelligence in project-based service learning to advance sustainable development: A pedagogical approach for marketing education. Marketing Education Review, 34(4), 307-323.

[11] Thontirawong, P., & Chinchanachokchai, S. (2021). Teaching artificial intelligence and machine learning in marketing. Marketing Education Review, 31(2), 58-63.

[12] Rogers, P. P., Allen, C., & Busby, A. (2024). Marketing Educators and Artificial Intelligence: A Perspective on Productivity and Innovation. Journal of Marketing Education, 02734753241299095.

[13] McAlister, A. R., Alhabash, S., & Yang, J. (2024). Artificial intelligence and ChatGPT: Exploring Current and potential future roles in marketing education. Journal of Marketing Communications, 30(2), 166-187.

[14] Allil, K. (2024). Integrating AI-driven marketing analytics techniques into the classroom: pedagogical strategies for enhancing student engagement and future business success. Journal of Marketing Analytics, 12(2), 142-168.

[15] Klementis, P. K. V. J. M. (2024). THE INTEGRATION OF THE DESIGN THINKING METHOD IN THE EDUCATIONAL MODELS OF THE MARKETING COMMUNICATION: HUMAN INNOVATION IN THE AGE OF ARTIFICIAL INTELLIGENCE. MARKETING IDENTITY, 339.

[16] Xia Sun,Xu Zhao,Yuan Ma,Xinrui Yuan,Feijuan He & Jun Feng. (2019). Muti-behavior features based knowledge tracking using decision tree improved DKVMN. (eds.)Northwest University, Xi'an, China;;Northwest University, Xi'an, China;;Northwest University, Xi'an, China;;Northwest University, Xi'an, China;;Xi'an Jiaotong University City College, Xi'an, China;;Northwest University, Xi'an, China

[17] Ruijun Liu,Yijun Zhang,Jieying Chen,Zhigang Wu,Yaohui Zhu,Jun Liu & Min Chen. (2025). BiAttentionNet: a dual-branch automatic driving image segmentation network integrating spatial and channel attention mechanisms. Scientific Reports,15(1),13193-13193.

[18] Yelan Wu,Pugang Cao,Meng Xu,Yue Zhang,Xiaoqin Lian & Chongchong Yu. (2025). Adaptive GCN and Bi-GRU-Based Dual Branch for Motor Imagery EEG Decoding. Sensors,25(4),1147-1147.

[19] Daniel Witschard,Kostiantyn Kucher,Ilir Jusufi & Andreas Kerren. (2025). Using similarity network analysis to improve text similarity calculations. Applied Network Science,10(1),8-8.