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PAPER

Vocational Education in the Era of Big Data: Course Design and Optimization Strategy Based on Educational Technology

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ABSTRACT

In the era of big data, vocational education is confronted with the challenge of effectively utilizing students' learning behavior data. With the advancement of information technology, the accumulation of students' learning trajectories and behavior data presents new opportunities for the optimization of education and teaching. Currently, many studies focus on the analysis of short-term learning behaviors, while comprehensive consideration of both long- and short-term behaviors remains insufficient, limiting the precision of course design and resource recommendations. Therefore, the exploration of an optimization strategy that integrates students' long- and short-term learning behaviors is urgently needed to enhance the effectiveness of vocational education. This study aims to propose a course design and optimization strategy based on educational technology, with a focus on integrating students' long- and short-term learning behaviors, thereby presenting corresponding resource recommendation methods and course design plans. The study will provide more personalized and precise teaching solutions for vocational education, promoting the enhancement of educational quality.

KEYWORDS

big data, vocational education, course design, learning behavior, resource recommendation, educational technology

1 INTRODUCTION

With the rapid advancement of information technology, big data has penetrated various industries, exerting particularly significant influence on the field of education. In vocational education, extensive amounts of students' learning behavior data have been generated, encompassing key information such as learning trajectories, study habits, and levels of knowledge mastery [1–5]. The effective utilization of this data to optimize teaching content and the allocation of learning resources has

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emerged as an important research topic within the current vocational education landscape [6–7]. Simultaneously, the ongoing progress of educational technology has facilitated the widespread adoption of intelligent education systems based on big data, providing new possibilities for course design and optimization in vocational education.

In this context, exploring course design and optimization strategies driven by big data holds significant practical relevance. On one hand, precise analysis of students' learning behavior data can provide educators with valuable insights, assisting in the adjustment of teaching strategies and content, thus enhancing educational outcomes [8–11]. On the other hand, the mining and analysis of big data can enable the personalized optimization of students' learning behaviors and outcomes, allowing vocational education to better align with individual needs and the direction of industry development [12–18]. Therefore, the exploration of effective course design and resource recommendation methods within a big data environment has become a critical research direction in the field of vocational education.

However, existing research have predominantly focused on the analysis of learning behaviors within singular timeframes, neglecting the interplay between students' long- and short-term learning behaviors. This oversight has resulted in insufficient precision and adaptability in resource recommendations and course design [19–21]. Furthermore, most methodologies have concentrated solely on the analysis of specific data types, failing to comprehensively integrate multidimensional learning behavior information, which has led to suboptimal outcomes in course optimization [22–23]. Therefore, addressing how to incorporate students' long- and short-term learning behaviors into course design and proposing more refined optimization strategies remains an urgent challenge.

This study, grounded in big data technology, combines students' long- and short-term learning behaviors to propose a resource recommendation method and an implementation strategy for course design and optimization. The first part of the study focuses on discussing the resource recommendation method that integrates long- and short-term learning behaviors to provide students with more personalized learning resources. The second part centers on how to design and optimize vocational education courses based on data from long- and short-term learning behaviors to enhance teaching effectiveness. This study aims to provide more intelligent and refined solutions for vocational education, promoting the development of educational technology applications in the era of big data.

2 PROBLEM DESCRIPTION OF COURSE DESIGN AND OPTIMIZATION IN VOCATIONAL EDUCATION

The goal of vocational education is to cultivate highly skilled talent, and these skills continually evolve with technological advancements and industrial upgrades. Therefore, big data-driven educational technology can track industry development trends and job requirements in real-time, helping vocational education courses to be updated promptly, ensuring that the skills students acquire closely align with actual job demands. With the rise of remote education and online learning platforms, technology-based course design can overcome temporal and spatial limitations, widely providing flexible learning resources, thus making vocational education more responsive to the learning needs and life rhythms of modern workers. Furthermore, students' learning behavior data and outcomes can be comprehensively recorded and analyzed through big data technology, laying the foundation for personalized teaching. As each student's learning style, pace, and interests differ, educational technology can utilize big data analysis to generate student profiles, facilitating targeted course design and optimization to enhance learning efficiency.

In this context, this study proposes a course design and optimization method that integrates students' long- and short-term learning behaviors, specifically applied to the field of vocational education. The core principle of this method lies in the in-depth analysis and modeling of students' learning behavior data through big data technology, enabling personalized course recommendations and designs. Initially, students' learning behaviors were categorized into long- and short-term components, which were modeled separately. Long-term learning behaviors reflect students' overall learning trajectories and interests; therefore, the model employs a self-attention mechanism to extract key features from these behaviors, capturing the deep-seated changes in students' long-term learning interests and behavioral patterns. Short-term learning behaviors reflect students' recent preferences and needs, which were modeled using gated recurrent units (GRUs) to accurately describe the dynamic learning states of students. The constructed model not only facilitates resource recommendations based on students' current learning needs but also optimizes future learning pathways according to long-term interests, ensuring that the recommended course content aligns with students' immediate interests while promoting their long-term developmental goals. This ultimately provides personalized course recommendations, optimizes the allocation of educational resources, and achieves more precise and intelligent teaching design and optimization in vocational education.

3 COURSE LEARNING RESOURCE RECOMMENDATION INTEGRATING STUDENTS' LONG- AND SHORT-TERM LEARNING BEHAVIORS

For student *i*, the sequence characteristics of his/her course learning behaviors can be represented as follows:

$$T(i) = \left\{n_1, n_2, n_3, \ldots, n_v\right\} \tag{1}$$

The long-term behaviors of student *i* were selected as $M(i) = n_1 \cup n_2 \cup n_3 \cup \ldots \cup n_{v-j}$, while the recent behaviors $n_{v-j+1}, n_{v-j+2}, \ldots, n_v$ were considered short-term behaviors. The model input consists of the long- and short-term course learning behaviors, candidate course learning resources *CA*, and other features *OF*, with the output being the online click probability of the candidate course learning resources. The model function expression is given as follows:

$$ZSE = D\left(M(i), n_{v-j+1}, \ldots, n_v, CA, OF\right) \tag{2}$$

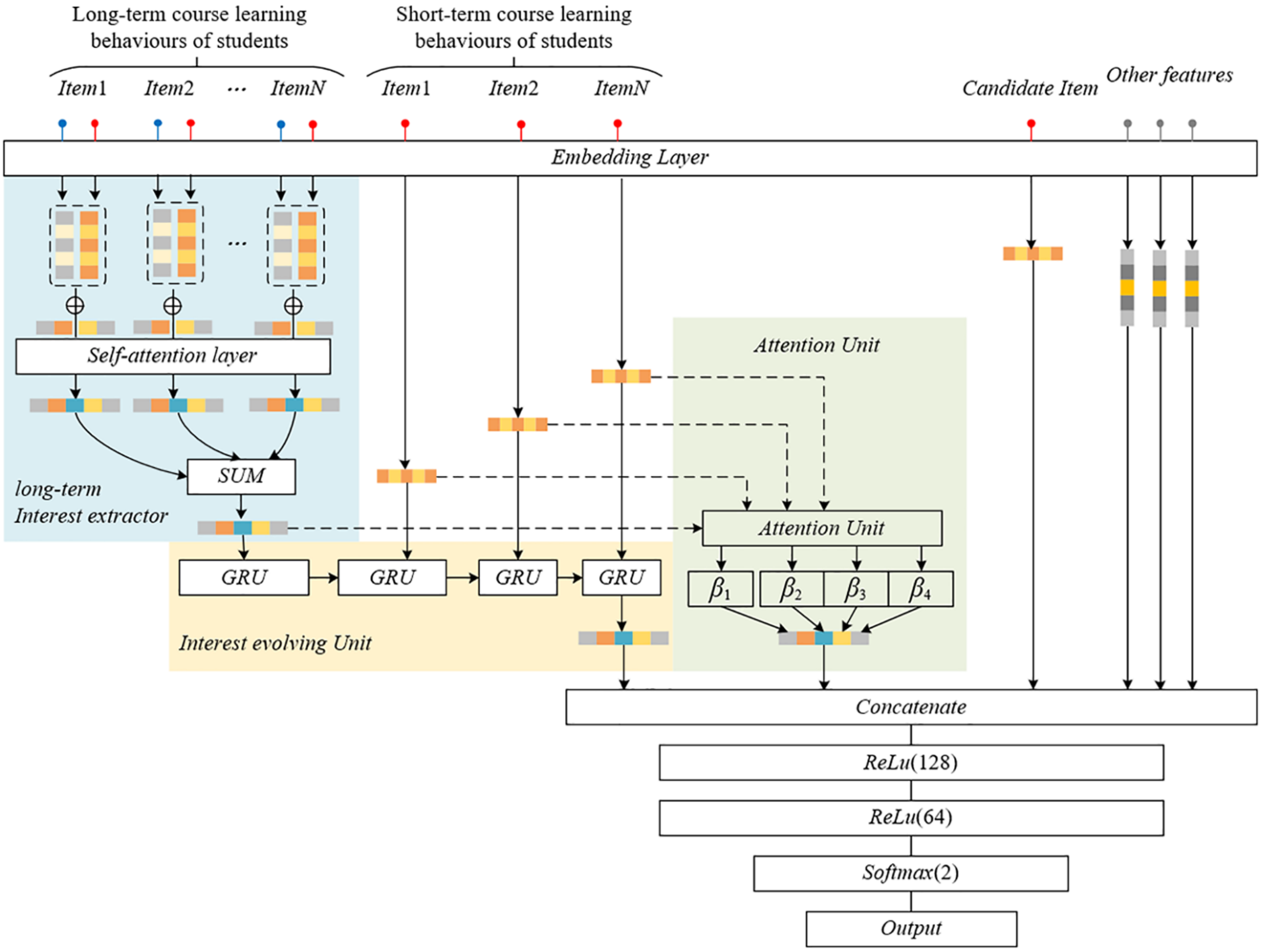

Fig. 1. Architecture of the effective recommendation model for personalized course learning resources

The key to course design and optimization lies in adequately considering how students' long- and short-term learning behaviors effectively inform personalized recommendations for course learning resources. Figure 1 illustrates the architecture of the recommendation model. The proposed model possesses two notable structural characteristics and functional advantages: a) The model partitions students' course learning behavior data into long- and short-term segments for separate modeling. By employing a self-attention mechanism to extract features from long-term course learning behaviors, the model captures students' stable preferences. This ensures a profound understanding of students' overall learning trajectories, providing a solid data foundation for personalized course design; b) Short-term course learning behaviors are directly input into the model and combined with long-term behavioral features. While modeling the sequence through GRU cells, a basic attention mechanism assigns weights to different learning behaviors, effectively reflecting students' current learning needs and interests.

The personalized recommendation mechanism of the proposed model enhances students' learning experiences and engagement, offering a more precise and intelligent course design solution for vocational education. This ensures that educational resources are flexibly allocated according to students' evolving needs and development, facilitating the realization of personalized learning. Specifically, the model consists of several key components: the input layer, the embedding layer, the long-term interest extraction layer, the interest evolution network, the attention unit, and the multilayer perceptron (MLP) layer. Each of these components is detailed as follows:

a) Input layer: The input layer of the model employs multidimensional features to comprehensively capture students' learning behaviors. Specifically, the input features are categorized into three types: students' long- and short-term course learning behaviors, and other relevant features. By analyzing the ordered sequence of learning behaviors, the model is able to extract the last *j* items as short-term course learning behaviors, while the remaining components are modeled as long-term course learning behaviors. Additionally, to enhance the expressiveness of long-term behavioral features, positional encoding was input alongside these features into the Transformer network, facilitating subsequent feature extraction and understanding. If the length of the ordered student behavior sequence is *n*, long-term course learning behaviors can be represented as follows:

$$n^M = \left(n_{IT}, n_{PO}\right) \tag{3}$$

$$M(i) = \left\{n_1^M, n_2^M, n_3^M, \ldots, n_{v-j}^M\right\} \tag{4}$$

Students' short-term behaviors $T(i) = \left\{n_{v-j+1}^T, n_{v-j+2}^T, \ldots, n_v^T\right\}$ were input directly into the network without positional encoding, where $n^T = n_{IT}$.

b) Embedding layer: The embedding layer within the model can effectively handle high-dimensional sparse one-hot encoded features by mapping them to a low-dimensional dense vector, thereby enhancing the efficiency and effectiveness of model training. The design of the embedding layer is akin to that of the Word2Vec model, allowing each one-hot code to be embedded into a fixed-size low-dimensional vector space. When processing students' long-term course learning behaviors, the embedding vector encompasses not only the features of course learning resources but also incorporates positional encoding information, ensuring that the model comprehensively understands the significance and contextual relationships of different courses within the time series. Specifically, the embedding matrix Q^M for long-term course learning behaviors has dimensions of $|N^M| \times f_M$, where f_M denotes the dimension of the embedding vector and $|N^M|$ represents the length of the behaviors. In a similar fashion, the embedding matrix Q^T for short-term course learning behaviors reflects the dense representation of its features, with dimensions of $|N^T| \times f_T$, while other features utilize a corresponding embedding matrix Q^P. Through this methodology, the model generates corresponding embedding vectors r_u^M, r_u^T and r_u^P for each course learning behavior, preserving the original feature information while effectively reducing computational complexity.

c) Long-term interest extraction layer: The long-term interest extraction layer within the model efficiently extracts features of students' long-term course learning behaviors using a Transformer layer based on the self-attention mechanism. Initially, this layer receives the long-term course learning behavior embedding vector *r* from the embedding layer. Through the self-attention mechanism, relationships between different learning behaviors can be captured, enabling the model to focus on students' learning preferences and patterns across various time periods. By employing multiple attention, heads, the model is able to learn multiple features simultaneously, thereby enhancing its expressive capacity. Figure 2 illustrates the architecture of the long-term interest extraction layer. Let the learnable parameters be represented by Q_w, Q_J and Q_N, and let the number of attention heads be denoted by g. All input long-term behavior embedding vectors of students are represented by R^M. The calculation process is outlined as follows:

$$HEAD_u = ATT\left(Q_w r_u^M, Q_J r_u^M, Q_n r_u^M\right) \tag{5}$$

$$T = LR(R^M) = CONCAT(HEAD_1, HEAD_2, ..., HEAD_g)Q_G \tag{6}$$

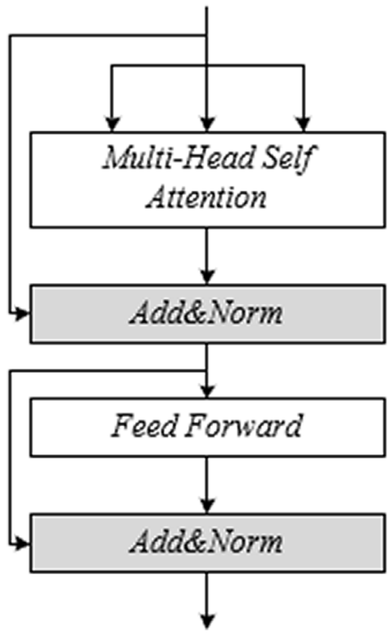

Fig. 2. Architecture of the long-term interest extraction layer

Following feature extraction, a feedforward network was employed to perform non-linear transformations, thereby further enhancing the model's fitting capability. To prevent overfitting, a dropout mechanism was incorporated into the design, which reduces the complexity of parameters during training. Additionally, residual structures and layer normalization (LN) were introduced within the self-attention module and the feedforward network to improve training stability and efficiency. Let the learnable parameter matrices be represented as $Q^{(1)}$ and $Q^{(2)}$, while the bias terms are denoted by $y^{(1)}$ and $y^{(2)}$. The non-linear transformation is expressed as follows:

$$D = FFN(T) \tag{7}$$

The residual structure and LN formulas are given as follows:

$$T' = LN(T + DROPOUT(LG(T))) \tag{8}$$

$$D = LN\left(T' + DROPOUT\left(RELU\left(T'Q^{(1)} + v^{(1)}\right)Q^{(2)} + y^{(2)}\right)\right) \tag{9}$$

Ultimately, a sum pooling operation was utilized to compress the features of the long-term course learning behavior sequences processed by the Transformer layer into a fixed-length vector. This ensures that the parameters fed into the MLP fully connected network have a consistent dimension. Let the extracted $^{M}_{u}$ after the Transformer layer be represented by d_u^M, and the final student long-term behavior features be denoted as R_{TR}^M, then the compression formula is as follows:

$$R_{TR}^{M} = SUMP(D) = SUMP\left(d_1^M, d_2^M, \ldots, d_{v-j}^M\right) \tag{10}$$

d) Interest evolution network: The interest evolution network within the model employs a GRU structure to dynamically predict the evolution of student interests. This network receives inputs including the vector R_{TR}^M, which represents the student's long-term characteristics, and the student's short-term course learning behavior vector r_u^T, processed through the embedding layer. By integrating these two features, the interest evolution network is able to capture trends in the changes of student interests, thereby facilitating a more precise understanding of their learning needs. If the number of student short-term behaviors is denoted as j, then the number of GRU memory cells is $j + 1$. The output from the last time step of the GRU unit is represented as R_{EV}, signifying the evolution results of all historical behaviors of the student. The calculation formula for the interest evolution layer is provided as follows:

$$R_{EV} = GRU\left(R_{TR}^M, r_{v-j+1}^T, r_{v-j+2}^T, \ldots, r_v^T\right) \tag{11}$$

e) Attention unit: The attention unit can effectively measure the weights of input course learning behaviors through a fundamental attention mechanism, thereby enhancing the accuracy of personalized course recommendations. The inputs to this unit include the embedding vector R_{CA} for candidate course learning resources and either the long-term course learning behavior embedding vector R_{TR}^M or the short-term behavior vector r_u^t of the student. By merging these two input vectors and their cross-features, the model captures the deep associations between student learning behaviors and candidate courses. In calculating the attention scores, the model employs a small neural network for feature mapping without applying SoftMax normalization. This design choice ensures that the resolution of the weights is not compressed, maintaining the significance of the weights associated with learning behaviors that are more relevant to the candidate course learning resources. Through this approach, the attention unit accurately reflects the student's preferences and focal points regarding different courses, providing a more flexible and precise basis for subsequent course recommendations. The model structure of the attention unit is illustrated in Figure 3. Assuming that the candidate item vector is represented by I and the student behavior vector by N, the final output of the attention unit is denoted as R_{AT}, with the calculation processes expressed as follows:

$$\beta_u = MLP\left(CONCAT(I, N, I - N, I \bullet N)\right) \tag{12}$$

$$R_{AT} = \sum_{u=1}^{v} \beta_u \cdot N \tag{13}$$

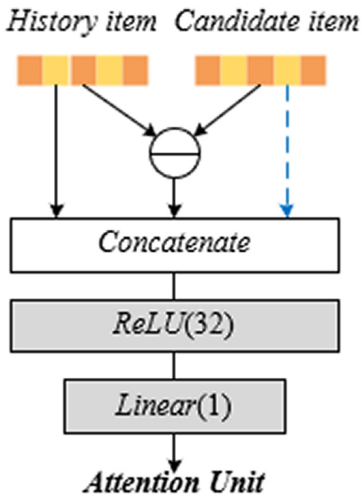

Fig. 3. Model of the attention unit

f) Multilayer perceptron layer: In the model, the MLP layer plays a crucial role in feature fusion and final prediction. This layer is responsible for concatenating the vector outputted from previous modules, integrating the rich feature information from the attention unit, the long-term interest extraction layer, and the interest evolution network. This process provides comprehensive input to the fully connected network, enabling the effective combination of various features to generate more accurate predictions. The design of the MLP layer ensures that different types of learning behavior features can interact and fuse within the same space, capturing the complex patterns of student learning in courses. Let R_{OT} denote the embedding vector of other features, R_{AT} represent the output vector from the attention unit, R_{EV} signify the output vector from the interest evolution network, and R_{CA} indicate the embedding vector of candidate items. The input to the MLP can be expressed as follows:

$$\varepsilon = CONCAT\left(R_{OT}, R_{AT}, R_{EV}, R_{CA}\right) \tag{14}$$

Ultimately, the output from the MLP was processed through a SoftMax layer, generating binary classification predictions, specifically the probability of a course being clicked. This probabilistic output provides a clear basis for personalized course recommendations, enabling the model to more accurately meet the learning needs of students. Let T represent a training set of size T, the output of the SoftMax layer be denoted by $o(a)$, and the true click probability of the training samples be represented by $b \in \{0,1\}$. Thus, the loss function can be formulated as follows:

$$LOSS = -\frac{1}{V} \sum_{(a,b)\in T} (b \log o(a) + (1-b)\log(1-o(a))) \tag{15}$$

4 COURSE DESIGN AND OPTIMIZATION INTEGRATING LONG- AND SHORT-TERM STUDENT LEARNING BEHAVIORS

The proposed system architecture for course design and optimization, which integrates both long- and short-term student learning behaviors, aims to construct an efficient and real-time recommendation system for personalized course resource recommendations. The system comprises multiple layers, with the first being the storage layer, responsible for storing vast amounts of data. Hadoop distributed file system (HDFS) was employed as the offline data warehouse for historical version data, while Hadoop database (HBase) was utilized for efficient real-time querying of structured data. MySQL and a remote dictionary server (Redis) were employed to handle student registration information and cache recommendation results, respectively, ensuring the real-time accessibility and reliability of the data. Figure 4 illustrates the specific system architecture.

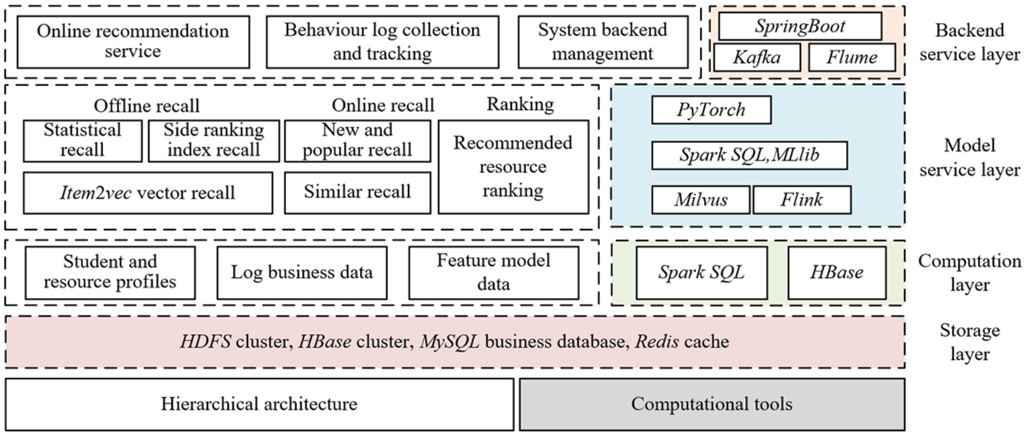

Fig. 4. Architecture of the course design and optimization system

The computation layer is responsible for transforming raw data into the formats required by the model service layer, which includes generating student profiles and course resource profiles to support the operation of multi-path recall algorithms and ranking algorithms. The model service layer focuses on the training and updating of the recall model and the ranking model, with the offline model updated as scheduled. In contrast, the real-time recall model dynamically generates recommendation sets based on student behaviors, thereby ensuring the timeliness of the recommendations.

The backend service layer is responsible for the online recommendation service interface and the operational logic of the system, ensuring seamless integration between the recommendation algorithms and the frontend display interface. This guarantees that students experience a smooth user interaction. The display layer directly interacts with the students, with their behavioral data collected via the logging module and fed back to the data warehouse, continuously updating the student profiles and providing a basis for future recommendations.

The system architecture was designed to integrate both long- and short-term student learning behaviors, ensuring that the recommendation system can respond in real time to students' evolving learning needs and interests. This allows for personalized course design and optimization, ultimately enhancing the learning experience and outcomes for students.

The workflow of the course design and optimization system can be divided into four main components: offline part, real-time part, data collection, and frontend part. The specific steps are as follows:

a) Data collection: When students browse the recommendation system website, their behavioral data can be captured through specific tracking points, generating behavior logs. These log data are collected by Flume and stored in the HDFS offline data warehouse, while also being sent to Kafka for use by the real-time recall module. Simultaneously, the business data from the backend database

MySQL is periodically synchronized to HDFS via Sqoop, ensuring the integrity of both offline and real-time data.

b) Data processing and profile generation: The logs and business data collected in HDFS can be processed using Spark SQL to generate student profiles, course learning resource profiles, and student behavior record tables. These data are stored in HBase for use by the multi-path recall model. Subsequently, student profiles and course learning resource profiles undergo further processing via Spark SQL, generating the feature data, which is also stored in HBase.

c) Offline recall and model training: The offline recall model generates corresponding recall results based on student profiles and course learning resource profiles, which are stored in HBase. To improve the efficiency of online services, the results of multiple recall algorithms are stored in the same HBase table, with different recall sets assigned to separate column families. The LSIN ranking model reads the student-course learning resource feature data from HBase for training and model updates. The trained model is deployed on Torch Serve, providing an external model prediction interface.

d) Real-time recall: The real-time recall model retrieves real-time student behavior data and new or trending course resource data from Kafka to generate similar recall results, which are stored in the recall table in HBase. Simultaneously, new and popular articles are cached in Redis to ensure fast access and efficient reading. These cached data are automatically deleted upon expiration.

e) Recommendation and feedback: When a student requests a recommendation, the recommendation center retrieves the recall set from the HBase recall table and passes it to the ranking model to predict the student's click-through rate on the recalled course learning resources. Based on the predicted click-through rates, the results are ranked and returned as recommendations. Most recommendation results are cached, while a smaller portion is displayed directly to the student. As students continue to interact with the system, a complete feedback loop is formed. This process not only ensures the accuracy and timeliness of the recommendations but also allows the system to continuously adjust and optimize to meet the evolving learning needs and behaviors of the students.

5 EXPERIMENTAL RESULTS AND ANALYSIS

The dataset used in this study comprises three main categories: 1) Teaching outcome data include student performance metrics such as final exam scores, class participation, and assignment completion. Additionally, student feedback and subjective evaluations of the course are collected through learning attitude surveys, providing further insight into teaching effectiveness. 2) Teaching process data record the specific operations and dynamics during the teaching process, which are essential for analyzing the implementation of course design and instructional strategies of teachers. Key indicators include lecture duration and pacing, the frequency and functionality of educational technology tools used, teaching strategies employed, and records of student interactions. 3) Learning environment data focus on the impact of the learning environment on course design and teaching outcomes, covering both physical and virtual environments. These data include the layout of learning spaces, the availability and usage of learning resources, technical support conditions, and student background information. The arrangement of learning spaces and the accessibility of resources can affect the student learning experience, while the stability of technical support is directly related to the effective application of educational technology.

Table 1. Performance comparison of different models in course learning resource recommendations

Model \ Dataset	Teaching Outcome Data		Teaching Process Data		Learning Environment Data	
	AUC	LogLoss	AUC	LogLoss	AUC	LogLoss
DCG	0.7652	0.5862	0.7845	0.5369	0.7784	0.5214
SVD+	0.7725	0.4956	0.8123	0.4123	0.8021	0.4456
GNN	0.7788	0.4231	0.8236	0.3987	0.8152	0.4326
BST	0.7896	0.4012	0.8254	0.3658	0.8236	0.4158
Model 1 (this study)	0.7841	0.4023	0.8236	0.3562	0.8254	0.4123
Model 2 (this study)	0.7796	0.4325	0.8235	0.3789	0.8125	0.4236
Model 3 (this study)	0.7726	0.5012	0.8124	0.4013	0.8123	0.4326

Table 2. Impact of different modelling approaches on area under the curve

Dataset	Method	AUC	Dataset	Method	AUC
Teaching outcome + teaching process data	Proposed model – attention mechanism	0.784	Learning environment data	Proposed model – attention mechanism	0.7785
	Proposed model – GRU structure	0.7625		Proposed model – GRU structure	0.7456
	Proposed model	0.8236		Proposed model	0.8236

Table 1 presents a performance comparison of various models in recommending course learning resources. By analyzing the performance of different models across teaching outcome, teaching process, and learning environment data, Model 1 from this study demonstrates strong overall performance. Notably, its area under the curve (AUC) value reaches 0.8236, and its logarithmic loss (LogLoss) is 0.3562 for teaching process data, highlighting its advantage in capturing students' learning dynamics. This indicates that the self-attention mechanism effectively enhances the model's understanding of the evolution of student interests when extracting long-term learning behavior features. In contrast, traditional models such as discounted cumulative gain (DCG) and singular value decomposition (SVD)+ exhibit inferior performance across multiple metrics, with AUC values generally below 0.78, reflecting their weaker adaptability in personalized recommendations. Further analysis of Model 2 and Model 3 reveals that, as the number of self-attention layers increases, the performance of the models fluctuates. Model 2 shows relatively stable overall performance and is suitable for handling complex learning behavior data, whereas Model 3 shows a slight deficiency in the AUC value for teaching outcome data. This may suggest that an excessive number of layers could lead to overfitting in certain situations, preventing the model from effectively leveraging the complexity of the data. Therefore, the findings of this study underscore the importance of selecting an appropriate number of self-attention layers to optimize the performance of the course recommendation system. This highlights the need to balance model complexity and generalization capability in the domain of personalized education.

Table 2 presents the impact of different modeling approaches on the AUC values. For models that integrate teaching outcome and teaching process data, the model using the attention mechanism demonstrates a higher AUC value of 0.784, while the model employing a GRU structure is significantly lower at 0.7625. This trend is also observed in the analysis of learning environment data, where the attention mechanism model achieves an AUC of 0.7785, compared to 0.7456 for the GRU-based model. These results suggest that when dealing with complex learning behavior data, the attention mechanism is more effective in capturing both long- and short-term learning dynamics. The analysis indicates that the attention mechanism offers a clear advantage in feature extraction and modeling student learning behaviors, thereby enhancing the predictive capability and adaptability of the model. Compared to the GRU structure, the attention mechanism is better equipped to identify critical information within the learning data, thus improving the effectiveness of personalized course recommendations.

Figure 5 illustrates the effect of different proportions of long- and short-term student learning behaviors on the effectiveness of course design and optimization of the model. As the proportion of long-term learning behaviors increases, the AUC value for teaching outcome data rises, reaching a peak of 0.822, with the best performance observed at a ratio of 16:4 (long-term/short-term). This indicates that the effective utilization of long-term behaviors significantly enhances the effectiveness of personalized recommendations. A similar upward trend is seen in the teaching process data, with the AUC reaching a maximum of 0.812, further supporting the positive impact of long-term learning behaviors on dynamic learning states. In contrast, the AUC for learning environment data exhibits less variation across different ratios, with the highest value being 0.784, suggesting that this data type is less sensitive to changes in the behavior ratio. The overall analysis indicates that increasing the proportion of long-term learning behaviors in the model contributes to improved accuracy in personalized course recommendations, particularly in the modeling of teaching outcome and process data. Long-term behaviors are more effective in capturing students' learning trajectories and evolving interests. This finding underscores the importance of appropriately balancing long- and short-term learning behaviors during course design and optimization to enhance model performance. In practical applications, prioritizing the influence of long-term learning behaviors is essential for optimizing learning resource recommendations and improving students' learning experiences.

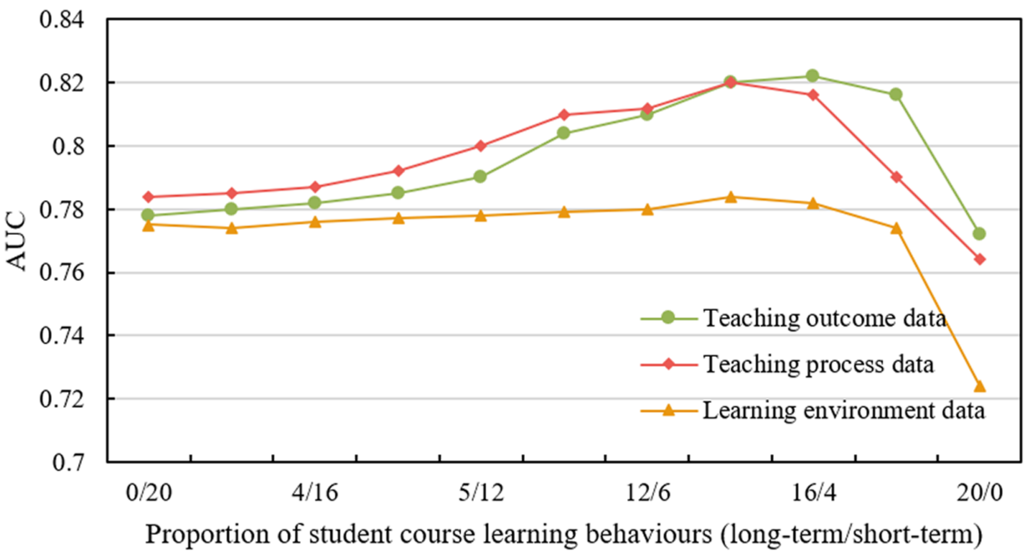

Fig. 5. Impact of the proportion of long- and short-term student learning behaviors on course design and optimization performance of the model

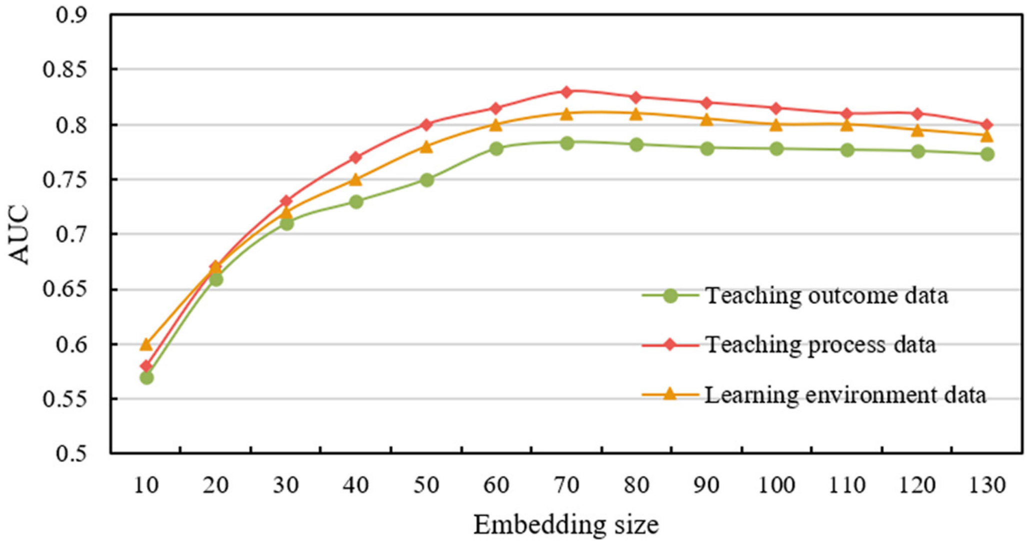

Fig. 6. Impact of the embedding size on course design and optimization performance (area under the curve) of the model

The data in Figure 6 show a clear upward trend in AUC values for teaching outcome data, teaching process data, and learning environment data as the embedding size increases. For teaching outcome data, the highest AUC value of 0.778 is achieved when the embedding size reaches 60, while for teaching process data, the peak AUC of 0.83 is observed at an embedding size of 70. This suggests that increasing the embedding size allows the model to capture the complex features of student learning behaviors more effectively. Furthermore, the AUC for learning environment data also demonstrates stability at an embedding size of 70, reaching a maximum of 0.81, further confirming the importance of embedding size in model performance. The overall analysis indicates that the appropriate selection of embedding size has a significant impact on model performance, particularly in capturing the multidimensional features of learning data. An embedding size that is too small may fail to adequately represent the complexity of student behavior, while an excessively large size may lead to increased computational costs and model redundancy. Therefore, it is recommended that an embedding size in the range of 60 to 70 be considered during course design and optimization to achieve optimal personalized recommendation results and enhance the efficiency of learning resource utilization. This finding provides practical guidance for model tuning, ensuring effectiveness in applications within vocational education.

6 CONCLUSION

This study, supported by big data technology, explored a resource recommendation method and a course design and optimization strategy that integrates both long- and short-term student learning behaviors, aiming to provide personalized and intelligent solutions for vocational education. In the first part of the study, the effectiveness of integrating long- and short-term learning behaviors in resource recommendations was validated through a performance comparison of different models, highlighting the importance of utilizing big data for in-depth analysis of learning behaviors. The second part examined how these behavioral data can be used to optimize vocational education courses, thereby improving teaching outcomes.

The experimental results demonstrate that both model selection and the appropriate choice of embedding size significantly impact model performance, particularly in terms of AUC values. These findings suggest that integrating long- and short-term learning behaviors not only improves the accuracy of recommendation systems but also provides more refined insights for course design. However, some limitations were identified, such as the potential impact of sample size and data diversity on the generalizability of the results. Future research could focus on larger datasets, more diverse learning environments, and more complex model structures to further enhance the effectiveness and adaptability of educational technologies. By continuing exploration and innovation, the progress and development of vocational education in the era of big data can be further promoted.

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