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PAPER

Optimizing Learning Path Design in Mobile Learning Platforms for Online Courses

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ABSTRACT

With the rapid advancement of information technology, online education, particularly vocational education, has become a vital avenue for enhancing skills and knowledge. Vocational education necessitates flexible and personalized learning path design to accommodate the diverse needs and behaviors of learners. Mobile learning platforms, as a pivotal form of modern online education, provide learners with the convenience of accessing educational resources anytime and anywhere. However, existing methods for optimizing learning paths exhibit notable limitations, primarily in accurately capturing learners' dynamic behaviors and in providing personalized and intelligent path design. Therefore, how to optimize learning paths based on learners' dynamic behavior data has become a research hotspot in academia and educational practice. At present, many studies focus on matching analysis based on students' static characteristics with course content but overlook learners' behavioral changes and dynamic needs during the learning process. Traditional recommendation algorithms and rule-based path design methods are difficult to cope with complex learning behaviors and diverse learner needs. This study addresses these limitations by proposing an optimization model for mobile learning path design based on multi-view prediction of dynamic student behaviors. The model extracts mobile interaction features from student groups, constructs a multiple mobile behavior collaborative encoder, and employs multiple task label prediction techniques to achieve personalized and intelligent optimization of learning paths. The results demonstrate that this approach significantly enhances the learning efficiency and experience of learners, offering novel insights and technological support for the path design of mobile learning platforms.

KEYWORDS

mobile learning platforms, learning path optimization, dynamic behavior prediction, personalized learning, vocational education, multi-label prediction

1 INTRODUCTION

With the rapid development of information technology, digital transformation has become a significant trend in modern education. Particularly in the field of

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vocational education, online learning has gradually emerged as an important means for training and skill enhancement [1–4]. The characteristics of vocational education necessitate a more prominent emphasis on personalized, flexible, and efficient learning. The challenge of leveraging information technology to improve learning outcomes has become a critical issue that needs to be addressed in the educational field [5–7]. The design of learning paths in online courses is one of the key factors influencing learning effectiveness, and mobile learning platforms provide learners with flexible and efficient learning methods, thus driving the rapid development of online education. Consequently, optimizing learning path design through scientific and rational approaches to enhance learning experiences and outcomes has become a focal point in current study on vocational education and online learning.

In mobile learning environments, learner behavior data is characterized by diversity and complexity. How to design the optimal learning path based on this data has become a key research area [8–11]. A well-designed learning path can help learners better acquire knowledge and improve learning efficiency. In vocational education, the optimization of learning paths can effectively align industry needs with learner characteristics, offering more targeted learning solutions [12, 13]. Although existing research has made progress in the design and optimization of learning paths, there remains a gap in realizing personalization and intelligence. Therefore, conducting in-depth research and proposing a dynamic optimization model based on student behavior data and the learning process is of significant importance for advancing personalized and intelligent learning path design in online learning.

Current study on learning path optimization mainly focuses on the analysis of the relationship between static student characteristics and course content, often neglecting the dynamic changes in learners' behaviors during the learning process [14–16]. Many methods rely on rule-based path design or traditional recommendation algorithms, but these approaches are often unable to capture the learners' immediate needs and changes in learning status accurately [17, 18]. Additionally, existing optimization methods tend to lack a deep analysis of behavioral differences within student groups and fail to account for the interactive effects between individual and group behaviors. As a result, these methods are limited in their ability to address the complexities of diverse learning scenarios and the varied needs of learners. This study proposes an optimization model for mobile learning path design based on multi-view dynamic behavior prediction of students, aiming to overcome the shortcomings of existing methods. The primary research content of this study includes four aspects: first, the definition of the mobile learning path design optimization problem, with clear optimization objectives and evaluation criteria; second, the extraction of mobile interaction features from student groups to analyze the behavioral patterns of learners during the learning process; third, the development of a multiple mobile behavior collaborative encoder that integrates multiple data sources to enhance the model's ability to predict dynamic student behaviors; and finally, the introduction of a task-based multi-label prediction method to achieve personalized recommendations for learning tasks. This study aims to provide a more intelligent and personalized learning path design method for mobile learning platforms, thereby improving learner outcomes and experiences and further advancing online vocational education.

2 DEFINITION OF THE MOBILE LEARNING PATH DESIGN OPTIMIZATION PROBLEM

In the context of online courses on mobile learning platforms, learner behavior is influenced not only by individual characteristics but also by the "contagion" effect of peer behavior. In a group setting, interactions and influences between students can cause changes in individual learning behaviors. Therefore, the consideration of behavioral interactions between student groups through dynamic behavior prediction has become a critical challenge in optimizing learning path design. To address this issue, a model for optimizing mobile learning path design based on multi-view student dynamic behavior prediction was proposed. This model conducts a comprehensive analysis of student behavior data from multiple perspectives, considering both the behavioral variations and mutual influences of learners across different tasks. This allows for an accurate prediction of each student's preferences for multiple perception task types, thereby enabling the design of personalized learning paths. The framework of the multi-view student dynamic behavior prediction model consists of three key components: student group interaction feature extraction, multi-behavior collaborative encoding, and multi-label prediction. The student group interaction feature extraction module first identifies the influencing factors within the group by analyzing the behavioral relationships and interactions between learners. These factors provide crucial inputs for optimizing personalized learning paths. The multi-behavior collaborative encoding module integrates behavior data from multiple learning tasks, employing a collaborative learning approach to model these interactions. This enables the model to capture the synergistic effects of student behaviors across different tasks and predict students' preferences for various learning tasks. Finally, the multi-label prediction module generates predictions of student preferences for each task type based on the outputs of the previous two modules, taking into account the multi-label characteristics of the tasks. This results in personalized task recommendations and learning path design for mobile learning platforms. This overall framework not only accounts for individual differences among students but also reflects the dynamic changes in group behaviors, fully optimizing the personalization and intelligence of learning path design.

In online courses on mobile learning platforms, the optimization of learning path design is a core issue for enhancing learning efficiency and personalizing the learning experience. Existing research typically focuses on static student characteristics, which, while providing some predictive value, change infrequently over time and are not always readily available. Therefore, the limitations of static features in capturing students' dynamic learning behaviors and real-time needs are evident. This study proposes a multi-view student dynamic behavior prediction method, which integrates mobile learning interaction network group behaviors. The goal is to achieve more precise and personalized learning path optimization through real-time capture of students' dynamic behaviors and analysis of group behavior interactions. Specifically, the proposed method integrates mobile learning interaction network group behaviors with multi-view student dynamic behavior prediction by analyzing behavioral patterns of students within mobile learning platforms. This approach extracts representative behavioral features, including frequently occurring "evaluation" and "star" behaviors, less frequent "favorite" and "fork" behaviors, and rarely observed "design" and "create project" behaviors. Through the analysis of these behaviors, students' dynamic preferences across different task types can be identified. These preferences exhibit clear time-based and frequency-based characteristics. The specific definitions involved in this method are outlined as follows:

Definition 1: Learning path optimization target sequence: In online courses on mobile learning platforms, the optimization problem of learning path design centers on how to formulate personalized learning paths based on students' historical learning behaviors and dynamic needs. To achieve this goal, learning path optimization target sequences can be defined by statistically analyzing the number and types of tasks each student engages with over a specific time period. More specifically, let $A^{iu} = \left\{a_1^{iu}, a_2^{iu}, \ldots, a_b^{iu}\right\}$ represent the changes and adjustments to student u's learning path each year over a period of B years, reflecting the frequency of participation in different learning tasks; $O^{iu} = \left\{o_1^{iu}, o_2^{iu}, \ldots, o_l^{iu}\right\}$ represents the trends in the changes of student u's learning path over L months, capturing learning preferences at different time intervals, and $W^{iu} = \left\{w_1^{iu}, w_2^{iu}, \ldots, w_f^{iu}\right\}$ represents the daily learning path choices of student u over F days, with task selection potentially changing on a day-to-day basis.

Definition 2: Group learning path collaboration sequence: In addition to the individual learning paths of students, the optimization of learning path design on mobile learning platforms must also consider the collective behavior of student groups and their collaborative effects. To comprehensively reflect the effectiveness of learning path design optimization, it is necessary to define a group learning path collaboration sequence. Specifically, let $A^H = \left\{a_1^H, a_2^H, \ldots, a_b^H\right\}$ represent the task participation of the student group over B years, reflecting the overall learning trend of the group; $O^H = \left\{o_1^H, o_2^H, \ldots, o_l^H\right\}$ represents the changes in the learning paths of the student group over L months, capturing the learning behavior patterns within the group across different time periods; and $W^H = \left\{w_1^H, w_2^H, \ldots, w_b^H\right\}$ indicates the frequency of task participation by the student group over F days, revealing the learning path preferences of the group across different time intervals.

Definition 3: Learning path preference prediction sequence: To further optimize learning path design and ensure the personalization and timeliness of task recommendations, the concept of a learning path preference prediction sequence was introduced in this study. Given students' historical behavior data and group behavior data, predicting a student's future learning path preferences under the current context is a crucial aspect of optimizing learning path design. Specifically, let the student behavior sequence $N^* = \{n_1, n_2, \ldots, n_m\}$ be defined, where each element in n_i represents a student's future preference for a particular type of learning task.

In the optimization of learning path design for online courses on mobile learning platforms, the central issue is how to develop personalized and efficient learning paths through accurate prediction of student dynamic behaviors, combined with group behavioral features. The problem under investigation can be specifically described as follows: Given a static mobile learning interaction network, individual behavioral sequences of students and group interaction sequences are used as inputs. Time series data processing methods are then applied to extract behavioral preference features. More specifically, student behavior data is aggregated at three-time granularities—daily, monthly, and yearly—forming time series with varying frequencies. At the same time, the group behavioral interaction sequence reveals the interactions and collaborative effects among students within the group. The dynamic changes in group behaviors are crucial for understanding students' learning preferences in a group context. By integrating this behavioral data from different time granularities, more accurate predictions can be made for the subsequent learning path design. Ultimately, the preference features derived from this fusion are used to predict individual student dynamic behaviors. Based on the prediction results, students' future task preferences are classified into different task labels, forming the dynamic behavior prediction sequence. These prediction sequences not only reflect students' learning interests and task choices over the upcoming period but also allow for dynamic adjustments based on students' behavioral interactions within the group. This enables the personalization and optimization of learning path recommendations. In terms of learning path design, the prediction results aid in tailoring task types and learning sequences to each student's individual learning needs, avoiding overly rigid or generic learning path arrangements. This maximizes both learning outcomes and the efficient use of platform resources.

3 EXTRACTION OF MOBILE INTERACTION FEATURES OF STUDENT GROUPS

The goal of extracting group student interaction features is to provide more precise data support for the optimization of personalized learning paths by deeply analyzing the interaction relationships between students and identifying common behavioral patterns within the group. Specifically, the mobile learning interactions formed through similar learning interests, behavioral habits, and learning needs among students not only reflect individual preferences but also reveal a "normalized" learning pattern at the group level. The interactions among students within the group extend beyond explicit communication to include implicit learning behavior connections, such as participation in the same tasks, task feedback, and other forms of engagement. To better utilize these internal group relationships, this study extracts group interaction features to capture students' learning tendencies, behavioral changes, and mutual influences within the group, thereby providing a basis for the group's collaborative effects in subsequent learning path recommendations. To achieve this goal, an attention mechanism was employed in this study. This mechanism calculates the similarity between students and their neighboring students in the mobile learning interaction network, thereby weighting the extraction of group behavior features. Within the attention framework, the influence value $x(i_u, i_k)$ between students represents the degree of behavioral influence that student k has on student u. This influence value can be calculated using a multi-layer perceptron (MLP) network. By combining the influence value with students' historical behavior data n and network parameters (j, q_1, and q_2), the similarity and interactive relationships between students in terms of learning task selection, learning progress, and other factors can be reflected.

$$x_{(i_u,i_k)} = j^S \tanh\left(q_1 n_{i_u} + q_2 n_{i_k}\right) \tag{1}$$

The attention value obtained was combined with the historical data of neighbouring student k to generate a new vector representation for student u:

$$n_{i_u} = n_{i_k} \cdot x_{(i_u,i_k)} \tag{2}$$

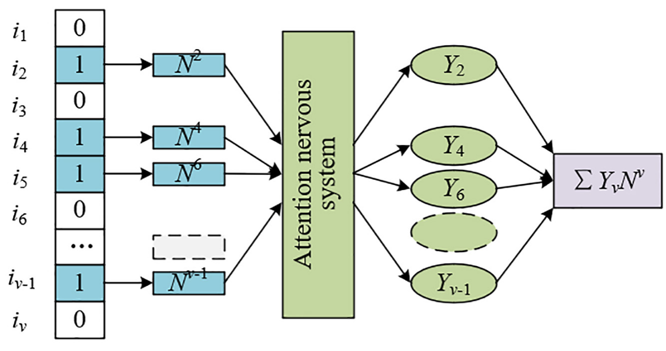

Fig. 1. Fusion representation of student group behavior

The roles students play within the group, their mobile learning interaction relationships with other students, and factors such as academic performance all influence their behavioral patterns and preferences. Therefore, it is crucial to account for the heterogeneity between students when extracting group behavior features. The influence of mobile learning interactions on different students must be considered. By introducing the attention mechanism, different weights were assigned to each student in the group, dynamically adjusting the fusion weight of individual students' behaviors based on the strength of their relationships with other group members. For students with strong mobile learning interaction influence, their behavioral patterns may have greater relevance to the overall group learning path design, and therefore, they were assigned higher weights. In contrast, students with weaker mobile learning interaction influence have relatively less impact on the group, and as such, they were assigned lower weights. Figure 1 illustrates the fusion representation of student group behavior. The softmax function was employed in this study to normalize the weights between student u and the V neighbors within the group H, with the following calculation:

$$x_{(i_u,i_v)} = \frac{\exp\left(t\left(n_{i_u}^{(e)}, n_{i_v}^{(e)}\right)\right)}{\sum_{v}^{V} \exp\left(t\left(n_{i_u}^{(e)}, n_{i_v}^{(e)}\right)\right)} \tag{3}$$

Assuming that the influence weight of neighbor i_v on student i_u is represented by $x_{(i_u,i_v)}$, the historical behavior data of neighbor i_v is denoted as $N_{i_v}^{(e)}$. When $e = 1$, $N_{i_v}^{(1)} = A^{i_v}$; when $e = 2$, $N_{i_v}^{(2)} = o^{i_v}$; and when $e = 3$, $N_{i_v}^{(3)} = W^{i_v}$. The fusion representation $HN^{(e)}$ of student behavior within group H is computed as follows:

$$HN^{(e)} = \sum_{i_v \in H} x_{(i_u,i_v)} N_{i_v}^{(e)} \tag{4}$$

4 MULTIPLE MOBILE BEHAVIOR COLLABORATIVE ENCODER

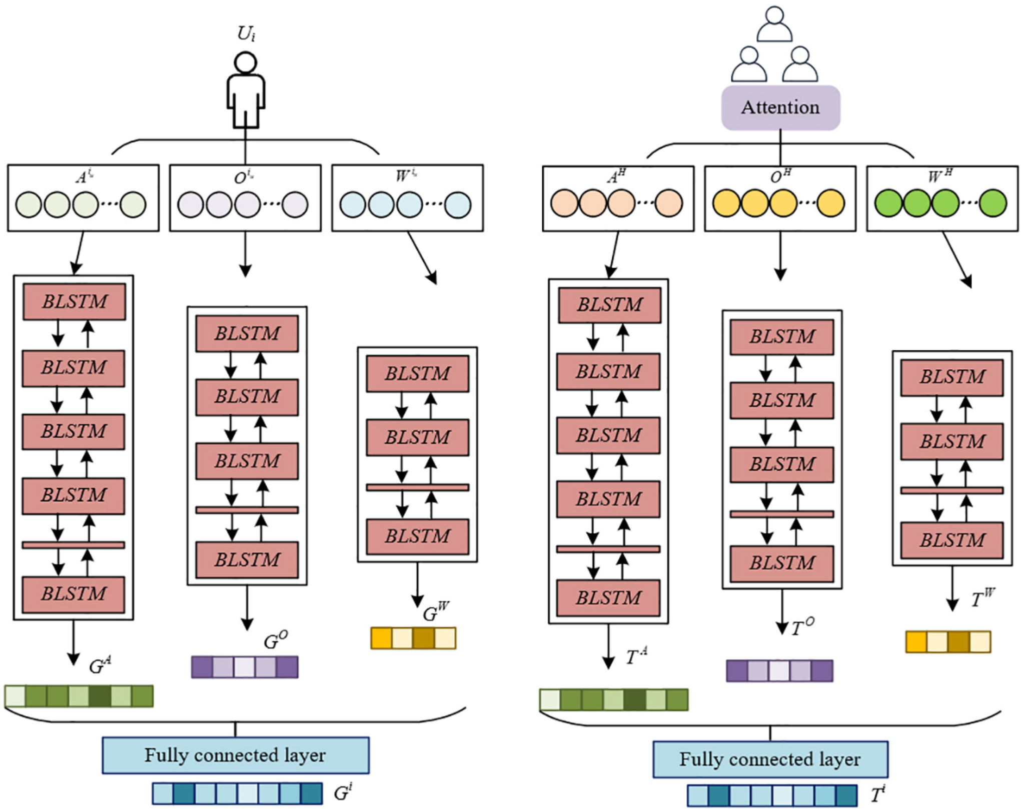

Fig. 2. Framework of multi-view user dynamic behaviour prediction method

The optimization of mobile learning path design requires the comprehensive exploration of students' multi-dimensional behavioral data. The behavioral data of students in mobile learning environments typically exhibit complex temporal relationships, where current actions are influenced by past behaviors, and future actions may impact present decisions. Furthermore, behavioral data often originates from various perspectives, including task engagement, group interaction, and personal interests. These views not only span different time intervals but may also contain hierarchical behavioral information. Traditional long short-term memory (LSTM) models, when processing time-series data, primarily rely on unidirectional feature propagation, considering only the dependency between the current and the previous time step. This approach may fail to capture the bidirectional relationships between actions when dealing with students' behavioral sequences. To address this limitation, the bidirectional LSTM (Bi-LSTM) network was chosen as the multiple mobile behavior collaborative encoder. By incorporating a backpropagation mechanism, Bi-LSTM captures the relationships between past and future behaviors at the same time step, thus enabling the simultaneous consideration of both contextual information from the past and the future. This allows for the effective integration of behavioral features across different time periods, facilitating the identification of latent associations between student behaviors within a multi-view learning process. The basic steps of the multi-view student dynamic behavior prediction model, as shown in Figure 2, are as follows:

a) Data preprocessing and feature extraction: The multiple types of behavioral data collected from students on the mobile learning platform were first preprocessed. These data typically include various perspectives, such as student participation in learning tasks, interactions with peers (e.g., comments, likes, and discussions), and fluctuations in personal interests. The data were organized into sequences of different time periods, such as daily, monthly, or quarterly data with different time granularities, and feature extraction was performed according to task-specific requirements.

b) Input to the Bi-LSTM network: After feature extraction, the behavioral data of students were input into the Bi-LSTM network. The input at each time step includes the student's behavioral data, encompassing multiple perspectives such as task engagement and interest changes. The Bi-LSTM network processes temporal information from both the past and the future, performing bidirectional encoding at each moment to compute the forward and backward dependencies of the behavioral data at that specific time.

c) Bidirectional information fusion: In the Bi-LSTM model, the output at each time step not only relies on the behavioral data at that time and its preceding data but also considers the behavioral data at that time and that which follows. This bidirectional information fusion enables the model to better understand the potential relationships between different time points in the behavioral sequence, thus allowing for a more comprehensive representation of student behavior. Specifically, at time step s, the hidden state outputs from the forward LSTM, denoted as $g_{s,d}$, and the backward LSTM, denoted as $g_{s,y}$, were combined to form the hidden state output of the Bi-LSTM at time s, i.e., $g_s = [g_{s,d}, g_{s,y}]$.

$$g_{s,d} = LSTM_d(Q, g_{s-1,d}) \tag{5}$$

$$g_{s,y} = LSTM_y(Q, g_{s-1,y}) \tag{6}$$

The historical behaviors of individual students over a specified period of *a* days, *b* months, and *c* years, namely A^{i_u}, O^{i_u}, and W^{i_u}, and the historical group behaviors A^H, O^H, and W^H, were encoded separately, resulting in the hidden states T^A, T^O, and T^W for the individual student and G^A, G^O, and G^W for the student group.

d) Output layer and multi-label prediction: Finally, the feature outputted by the Bi-LSTM network, which was generated by fusing both forward and backward information, formed a comprehensive behavior feature representation. These features were then used for multi-label prediction, which forecasts the future behavioral patterns of the student. The multi-view behavior features of each student were processed by the network, and the model was capable of personalizing the recommendation of suitable learning paths and task types for each individual student.

5 MULTI-LABEL PREDICTION OF TASKS IN MOBILE LEARNING PLATFORMS

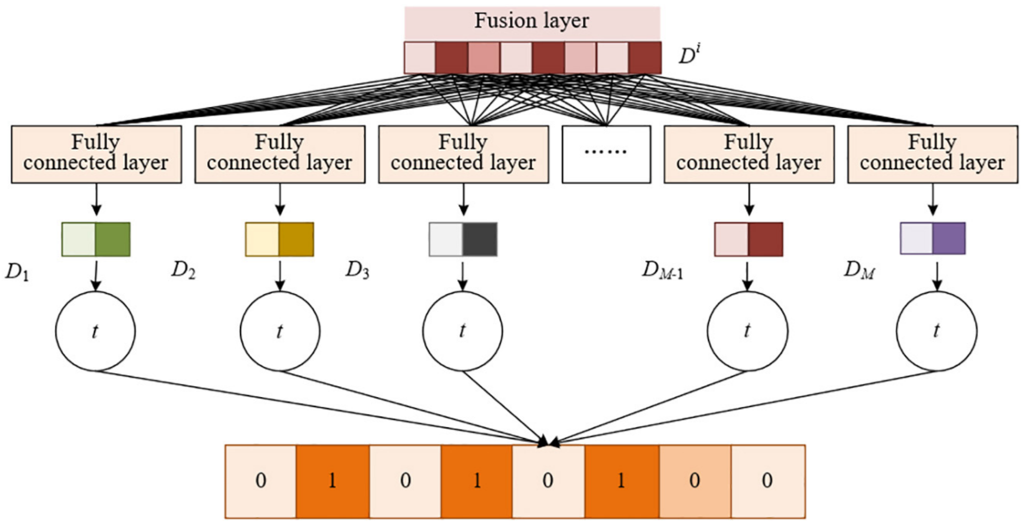

Fig. 3. Framework for the mobile learning path design method

In mobile learning platforms, each student may experience dynamic changes across multiple aspects, such as learning tasks, interactive behaviors, and interest preferences. These behaviors are not necessarily mutually exclusive but may intersect or overlap. Therefore, traditional single-label classification methods are not effective in handling scenarios with multiple tasks or labels. Multi-label classifiers, on the other hand, are capable of predicting multiple behaviors of a student simultaneously, especially when the student's behavior sequence exhibits various possibilities. This approach provides more accurate learning path optimization strategies. Figure 3 illustrates the framework for the mobile learning path design method. Based on the principles of multi-label classification, the behavior sequence of a student was treated as multiple binary classification problems in this study. Predictions for each label were used to capture the diverse behavioral information of the student. For each student's behavior pattern, the sigmoid activation function was employed instead of the softmax function, as it allows for independent predictions for each label. This enables the model to independently assess whether each task, behavior, or interest will occur, without interference between predictions. In the specific context of classroom learning on mobile learning platforms, students may be interested in different types of tasks simultaneously or may exhibit high engagement in certain tasks while showing weaker involvement in others. By utilizing the sigmoid output layer, the model predicted an independent label for each task or behavior, thus generating a multidimensional learning path recommendation. Furthermore, during the training process, the cross-entropy loss function was used to optimize the accuracy of each label's prediction, ultimately enabling the design of more precise, personalized learning paths for students. Let $D_k^{i_u}$ represent the output of the k-th fully connected layer for student u, with the parameters trained in this layer denoted as Q_k and y_k. Let V denote the total number of training samples, M represent the total number of task categories, and $B_k^{i_u}$ indicate whether the u-th student is interested in the k-th mobile learning platform task category. The preference probability of the u-th student for the k-th task category is denoted as $\delta\left(D_k^{i_u}\right)$. The following equations hold:

$$D_k^{i_u} = Q_k^S g_s + y_k \tag{7}$$

$$LOSS = -\frac{1}{V}\sum_{u}^{V}\frac{1}{M}\sum_{k}^{M}\left(B_k^{i_u} * \log\left(\delta\left(D_k^{i_u}\right)\right)\right) + \left(\left(1 - B_k^{i_u}\right) * \log\left(1 - \delta\left(D_k^{i_u}\right)\right)\right) \tag{8}$$

6 EXPERIMENTAL RESULTS AND ANALYSIS

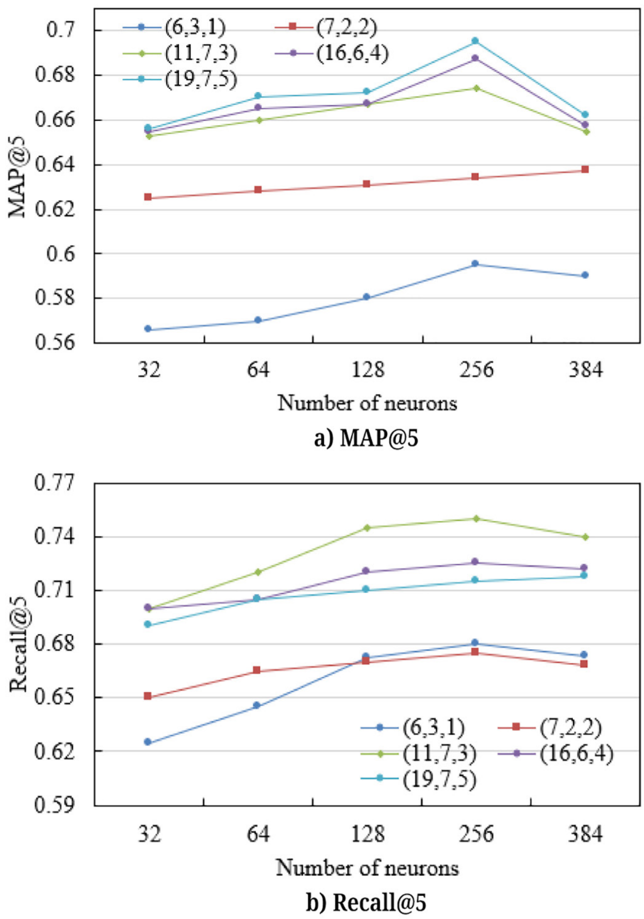

Fig. 4. Experimental results under different hyperparameter settings

The model for optimizing mobile learning paths based on multi-view student dynamic behavior prediction was systematically evaluated through experiments conducted with various hyperparameter settings. The experimental results shown in Figure 4 indicate that both MAP@5 and Recall@5 metrics exhibit favorable trends under different configurations of neuron counts and network architectures. Particularly, with the configuration of (19, 7, 5), as the number of neurons increases, MAP@5 reaches 0.695, showing a significant improvement and maintaining a high performance relative to other configuration setups. Similarly, Recall@5 also performs excellently, achieving a maximum of 0.745. This suggests that the model is highly capable of accurately capturing learner behavior characteristics and recommending personalized learning tasks. Overall, it is evident that as the number of neurons increases, the model's performance improves, especially under more complex network structures, highlighting the importance of deeper feature extraction capabilities for enhanced model performance.

Table 1. Performance comparison of different mobile learning path design methods

Model	MAP@10%		Recall@10%		F1@10	
	AVG	SD	AVG	SD	AVG	SD
MPC	0.3215	0.2114	0.3625	0.2135	0.3321	0.0018
MCTS	0.5784	0.1425	0.6215	0.1244	0.5845	0.0012
LSTM	0.5236	0.1562	0.5895	0.1325	0.5521	0.0014
Proposed model	0.8124	0.1236	0.8231	0.1240	0.8213	0.0011
Second-best	0.5748	0.1325	0.6254	0.1326	0.5895	0.0012
First-best	0.8236	0.1245	0.8216	0.1258	0.8215	0.0008
Relative gain	0.2459	0.0081	0.2158	0.0189	0.2365	0.0005

In the performance comparison of different mobile learning path design methods, the proposed model based on multi-view student dynamic behavior prediction demonstrates significant advantages. Specifically, as shown in Table 1, the proposed model achieves a MAP@10% of 0.8124, significantly outperforming other methods such as model predictive control (MPC) (0.3215), LSTM (0.5236), and Monte Carlo tree search (MCTS) (0.5784), as well as the second-best (0.5748) and first-best (0.8236) configurations. This result indicates that the proposed model is more effective in identifying and predicting learner behavior patterns, thereby optimising mobile learning paths. Additionally, the average Recall@10% and F1@10 values are 0.8231 and 0.8213, respectively, further confirming the model's efficiency in personalizing learning task recommendations. In contrast, the performance of other methods does not reach similar levels, particularly MPC, which has a Recall@10% of only 0.3625, significantly lower than that of the proposed model. By integrating multiple data sources and extracting student group mobile interaction features, the proposed model significantly improves the accuracy of task prediction and personalized adaptation. The experimental results not only reflect the rationality of the defined optimisation goals and evaluation criteria but also highlight the model's potential for application in real educational environments.

Table 2. Performance comparison of different mobile learning path design methods on different datasets

Data	Evaluation Metric	MPC	MCTS	LSTM	Proposed Model
Course dataset	MAE	0.6652	0.6528	0.6235	0.6189
	RMSE	0.8541	0.8451	0.8154	0.8026
Learning dataset	MAE	1.1235	1.3256	1.1254	1.1145
	RMSE	1.2548	1.2345	1.1268	1.0256
Textbook dataset	MAE	0.8452	0.8326	0.8256	0.7895
	RMSE	1.1246	1.1284	1.1214	1.1124

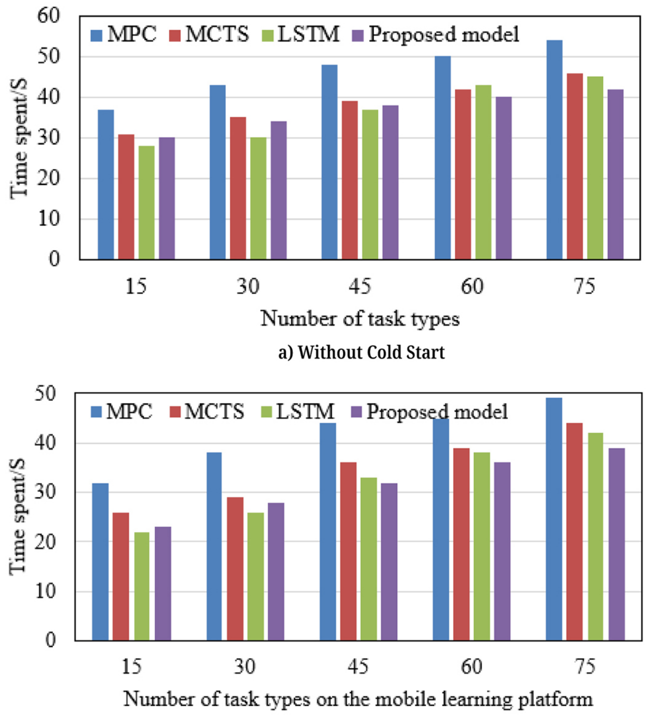

Fig. 5. Comparison of algorithm running time and number of task types on the mobile learning platform

In the performance comparison of mobile learning path design methods across different datasets, the proposed model based on multi-view student dynamic behavior prediction consistently outperforms other approaches in multiple evaluation metrics. As shown in Table 2, on the course dataset, the proposed model achieves a mean absolute error (MAE) of 0.6189, which is superior to MPC (0.6652), MCTS (0.6528), and LSTM (0.6235). The root mean squared error (RMSE) metric also shows significant improvement, reaching 0.8026, which is notably lower than that of MPC (0.8541), MCTS (0.8451), and LSTM (0.8154). On both the learning dataset and textbook dataset, the proposed model demonstrates a substantial reduction in MAE and RMSE values compared to the other methods. Particularly on the learning dataset, the MAE and RMSE of the proposed model are 1.1145 and 1.0256, respectively, highlighting its stability and accuracy in more complex learning environments.

As shown in Figure 5, when cold start is not employed, the proposed model demonstrates superior performance across different task types on the mobile learning platform. With 15 task types, the model is able to complete 30 tasks, while MPC, MCTS, and LSTM complete 37, 31, and 28 tasks, respectively. Although the model's task completion count is still somewhat lower, it exhibits a relatively steady growth as the number of task types increases, demonstrating strong adaptability. When the number of task types reaches 60, the model completes 40 tasks, compared to 50 tasks for MPC and 42 tasks for MCTS. Although the number of tasks completed is still slightly lower, a gradual performance improvement is observed. Compared to LSTM, the proposed model consistently shows more stable growth across all task types, particularly when the number of task types reaches 75, where the model completes 42 tasks, closely approaching MPC's 54 tasks, indicating its feasibility under high task complexity.

In summary, the proposed mobile learning path design optimization model based on multi-view student dynamic behavior prediction demonstrates relatively stable performance growth when facing different task types. While the task completion count is slightly lower than that of MPC, the model shows distinct advantages in overall adaptability and scalability. Through the construction of a multiple mobile behavior collaborative encoder and the application of multi-label prediction methods, the model is able to handle complex learning tasks more effectively, providing learners with personalized learning path recommendations.

7 CONCLUSION

This study proposes an optimized model for mobile learning path design based on multi-view student dynamic behavior prediction, aiming to address the limitations of existing mobile learning approaches in terms of personalized recommendation and dynamic adaptability. The study is divided into four main components. First, the optimization problem of mobile learning path design and its evaluation criteria were defined. Second, by extracting mobile interaction features from student groups and analyzing learner behavior patterns throughout the learning process, the dynamic needs of learners were revealed. Third, a multiple mobile behavior collaborative encoder was constructed to integrate data from multiple perspectives, thereby enhancing the model's ability to predict student dynamic behaviors. Finally, a task-based multi-label prediction method was proposed to achieve personalized learning task recommendations and provide more accurate learning path suggestions for students. Experimental results demonstrate that the proposed model outperforms traditional methods across various hyperparameter settings and in comparisons with other mobile learning path design methods, particularly showing stronger stability and adaptability as task complexity increases.

Overall, this study holds significant theoretical and practical value, offering a model and new insights for personalized teaching in the field of mobile learning. However, certain limitations exist, such as the need for further validation of the model's generalization capability in specific scenarios and the enhancement of its real-time data processing ability. Future research can focus on further optimizing the model's real-time predictive capabilities, extending it to a broader range of learning scenarios and task types, and considering additional external factors that influence student learning behaviors, all of which will contribute to improving the model's overall performance and practical applicability. This will support the intelligent development of mobile learning systems, leading to a more personalized and efficient learning experience.

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