

# Strategies for Optimizing Personalized Learning Pathways with Artificial Intelligence Assistance

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**Abstract**—With the deepening application of artificial intelligence (AI) in the field of education, Personalized Learning Pathways (PLPs) as a strategy to revolutionize traditional educational models have garnered widespread attention. This paper aims to explore strategies for optimizing PLPs with the aid of AI, in order to enhance learning efficiency, stimulate students' interest in learning, and foster their holistic development. The background section discusses the "one-size-fits-all" teaching methods prevalent in traditional education models and the importance and necessity of PLPs. Following this, the study delves into the limitations of existing methods for optimizing PLPs, especially in terms of dynamic adaptability and real-time feedback mechanisms. The paper consists of two main parts: the first part constructs a dynamic model to simulate the impact of PLP design features on the student learning process; the second part proposes a dynamic PLP resource recommendation algorithm based on incremental learning. By updating students' abilities, preferences, and knowledge states in real-time, the algorithm can provide more precise learning resource recommendations. The experimental results demonstrate that the proposed dynamic PLP resource recommendation algorithm based on incremental learning exhibits significant effects in optimizing PLP design. It can improve the accuracy of the recommendation system and positively influence the long-term learning state transition of students. This proves the potential and practical application value of dynamic models in the field of personalized education. The methods and findings of this study not only enrich the theoretical foundation of the field of personalized learning but also offer robust technical support for practical educational practices, holding significant academic and practical value.

**Keywords**—Personalized learning pathways (PLPs); artificial intelligence (AI); dynamic model; incremental learning; resource recommendation

## I. INTRODUCTION

In today's era of rapid technological advancement in educational technology, AI has become an important driving force behind innovation and reform in education [1-3]. Traditional education models often adopt a "one-size-fits-all" teaching strategy, neglecting the importance of individual differences among students. With the maturity of big data and machine learning technologies, the concept of PLP has gradually emerged, aiming to tailor learning paths for each student to meet their unique learning needs, abilities, and interests. This approach promises to completely transform traditional education models, providing learners with a more precise and efficient learning experience [4-7].

Optimizing PLPs can not only improve students' learning efficiency and quality but also stimulate their interest in learning and enhance their self-driven learning motivation [8, 9]. In this context, exploring how to utilize AI to assist in PLP holds great practical significance and profound social impact in promoting the comprehensive development of students' abilities and narrowing the educational gap [10-13]. However, the PLP design is not a simple technical issue; it also involves the comprehensive application of complex disciplines such as educational psychology and cognitive science.

In the existing literature, the design and optimization of PLPs have become an important research direction in the field of educational technology. However, despite some progress in theory and practice, there are still many deficiencies and challenges. Specifically, most PLP designs lack adaptability to the dynamic changes in student learning, relying too heavily on static data and ignoring real-time feedback and changes in the learning process [14,15]. For example, many studies use static data that only reflects the student's learning state at a particular moment, failing to fully consider the dynamic changes in the student's learning process. This approach makes it difficult to address the constantly changing needs and states of students during the learning process, resulting in a lack of flexibility and adaptability in PLP design. Additionally, existing recommendation systems typically use batch learning methods, which are highly efficient in processing large-scale data but neglect the incremental updates of students' abilities, preferences, and knowledge states [16,17]. The batch learning method implies that the system can only update its recommendation strategy at predetermined batch intervals, which fails to reflect the students' latest learning situation in real-time, resulting in a lag between the recommendation results and the students' actual learning state. As students progress in their learning and accumulate knowledge, their learning needs and interests change, but the lag in batch learning methods makes it difficult for recommendation systems to promptly adjust recommended content, affecting learning effectiveness.

Traditional PLP design typically relies on static data and cannot adapt to the dynamic changes in students' learning states. This paper proposes a dynamic model in Section II that can capture students' learning states and needs in real-time. This innovation allows PLP design to respond more flexibly to students' real-time feedback and changes, improving the accuracy and effectiveness of personalized recommendations. Existing recommendation systems mostly use batch learning methods, failing to fully consider the dynamic changes in

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students' abilities, preferences, and knowledge states. In Section III, this paper proposes a dynamic PLP resource recommendation algorithm based on incremental learning, which can continuously optimize recommendation results using real-time data, ensuring that learning content always remains in sync with the students' current state. This approach can more accurately reflect the students' latest learning situation, significantly improving the accuracy of personalized learning.

This paper fills a gap in existing academic research by introducing dynamic models and incremental learning algorithms, proposing a more refined and dynamic method for optimizing PLPs. This research provides new directions and insights for future personalized learning research, promoting the development of educational technology. At the same time, the research results of this paper have significant application value. By capturing students' learning states and needs in real-time and continuously optimizing learning paths using incremental learning algorithms, educators can provide more personalized and effective teaching services. This not only improves the effectiveness and experience of student learning but also better meets the needs of individualized education, promoting educational equity and quality improvement.

The construction of the dynamic model used in this paper is an important concept in the field of AI, particularly in machine learning and data mining. This model can dynamically adjust and predict students' learning states and needs based on real-time data. The proposed dynamic PLP resource recommendation algorithm based on incremental learning can continuously optimize recommendation results using real-time data, ensuring that learning content remains in sync with the students' current state. This is precisely the strength of AI in handling dynamic data and real-time feedback. Personalized recommendation systems are a classic application of AI and machine learning. By analyzing user behavior and preferences, recommendation systems can provide personalized content for users.

## II. CONSTRUCTION OF A DYNAMIC MODEL FOR THE IMPACT OF PLP DESIGN FEATURES ON THE STUDENT LEARNING PROCESS

To adapt to students' personalized learning needs and optimize learning pathways, this study uses a Non-Homogeneous Hidden Markov Model (NHMM) to capture the complexity of students' learning dynamics [18,19], further constructing a dynamic model for the impact of PLP design features on the student learning process. This allows for a deep understanding and accurate simulation of how PLP can be adjusted in real-time to adapt to students' constantly changing learning states, abilities, and preferences. NHMM allows us to observe how the learning states of students evolve over time and considers how micro-decisions in PLP affect learning behavior and outcomes. Through this dynamic model, this paper can reveal the interactions between learning pathway design features, such as progressive content difficulty, interactive learning elements, personalized feedback mechanisms, and students' learning processes, thereby achieving real-time optimization of learning pathways. Fig. 1 presents the conceptual model.

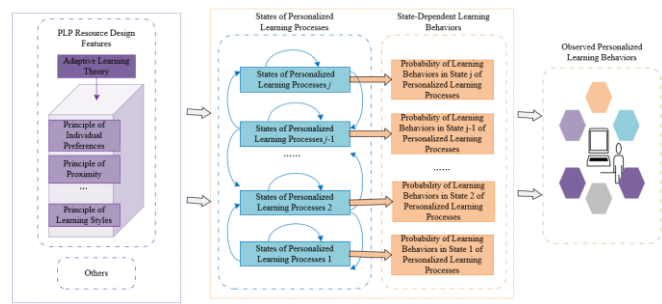


Fig. 1. Conceptual model of the impact of PLP resource design features on the learning process

To precisely capture and respond to subtle changes in student learning behaviors, thereby allowing for real-time adjustments in learning pathway design features such as course difficulty, content diversity, interactivity, and feedback timeliness, this paper considers each learning pathway as an observation subject with learner behaviors on it serving as evidence of the learning process. Through observation and analysis of learning behaviors at each stage, it is possible to dynamically reveal the specific correlations between PLP and student learning outcomes, thereby providing targeted optimization suggestions.

Specifically, assume that the hidden learning state of a student at moment  $s$  is represented by  $T_s$ , and the specific behavior of the student on learning pathway  $u$  observed at the same moment is represented by  $b_{s,u}$ . For each learning pathway  $u$ , there is a fixed sequence of learning states  $T_u = T_{u1}, T_{u2}, \dots, T_{us}$ , where  $T_{u1}$  is the initial state of learning pathway  $u$ , and each state  $T_{us}$  belongs to the state space  $1, 2, \dots, v$ , along with a corresponding sequence of observed results  $b_u = b_{u1}, b_{u2}, \dots, b_{us}$ . Given the state sequence  $T_u$  and the set of model parameters  $\eta$ , our focus is on the probability of observing the behavior sequence  $b_u$ . The model focuses on dynamically adjusting and optimizing learning pathways through PLP design features, such as task difficulty adjustments and content recommendation algorithms, to adapt to students' changing learning needs and predict the likelihood of their learning behavior state transitions. With  $T_u$  and  $\eta$  given, the probability of  $b_u$  can be calculated as follows:

$$O(b_u / \eta, T_u) = \prod_{s=1}^s O(b_{us} / \eta, T_{us}) \quad (1)$$

It can be attained that  $O(b_u / \eta, T_u) = x(b_{u1} | T_{u1}) * x(b_{u2} | T_{u2}) * \dots * x(b_{us} | T_{us})$ , and it's observed that the probability of result  $b_{us}$  is  $x(b_{us} | T_{us})$ , which is an element of the probability vector  $X(u, s)$ .

Further calculation involves the probability of the simultaneous occurrence of the learning state sequence and the student behavior result sequence. Specifically,  $w(T_u | \eta)$  represents the probability of the occurrence of the state sequence  $T_u$  for a student following a specific learning pathway  $u$  under the given set of model parameters  $\eta$ . This probability is derived from the multiplication of the initial state probability  $\tau_u$  of  $T_u$  and the elements  $w(T_{us}, T_{us+1})$  of the state transition probability matrix  $W_{us-s+1}$ , reflecting the likelihood of a student moving from one learning state to the next. The PLP design

proposed in this paper emphasizes adjusting teaching strategies based on real-time feedback and learning states of students to achieve a more efficient learning process. The probability of the simultaneous occurrence of  $b_u$  and  $T_u$  can be calculated through the following formula:

$$O(b_u, T_u / \eta) = O(b_u / \eta, T_u) O(S_u / \eta) \quad (2)$$

We calculate the total probability of observing a specific behavior result sequence  $b_u$  by summing over all possible learning state sequences. Within the framework of a Hidden Markov Model, each state in a PLP has an initial probability, and each state transition corresponds to a probability value. The cumulative product of these probability values represents the pathway probability from the initial state through a series of transitions to the final state. Summing all possible pathway probabilities yields the total probability of a student's continuous learning on a PLP. The specific calculation formula is as follows:

$$M(b_u) = O(b_u / \eta) = \sum_{\forall T_u} O(b_u / \eta, T_i) O(T_u / \eta) \quad (3)$$

This calculation process not only includes the dwell time of students in each state but also considers how pathway design features (such as content difficulty, teaching methods, resource types, etc.) affect the transition and continuity of learning states. Thus, this sum is not just a numerical accumulation but represents a complex dynamic system's probability, incorporating student behavior data, personalized educational interventions, and learning outcome feedback.

Model state transitions are set as a stochastic process restricted to adjacent states to ensure the continuity and logic of learning pathways. By setting the transition probabilities to zero for non-adjacent states, the model strictly limits the possibilities for learners' state transitions, ensuring that students can only move from their current state to an adjacent state at any given moment  $s$ . The design features of PLP, such as the difficulty level of teaching content, the presentation mode of learning materials, and the type of learning activities, are all reflected through the state transition matrix  $W_{ts-1-ts}$ , influenced by students' real-time feedback  $E_s$  and determining the possibility of students' state transitioning from moment  $s-1$  to moment  $s$ . In this framework, PLP design adjusts the state transition matrix dynamically to adapt to each student's learning needs and preferences, thereby affecting the probability distribution of a student reaching a specific state  $j$  at moment  $s+1$ . Suppose the conditional probability of state transition is represented by  $w(k,j) = w(T_s=k, T_{s+1}=j) = O(T_{s+1}=j | T_s=k)$ , the following formula defines the state transition matrix:

$$W(s, s+1) = \begin{pmatrix} w(1,1) & w(1,2) & 0 & \dots & 0 & 0 \\ w(2,1) & w(2,2) & w(2,3) & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & w(j, j-1) & w(j, j) \end{pmatrix} \quad (4)$$

Assuming the student's state placement matrix is represented by  $W_{ss}$ , the state transition matrix by  $W_{ts-1-ts}$ , the lower critical point of state  $j$  by  $\omega_{jm}$ , and the upper critical point

of state  $j$  by  $\omega_{js}$ , and always  $\omega_{js} > \omega_{jm}$ , then there is the transition probability distribution for  $T_{s+1}=j$ :

$$\begin{aligned} w_{j \rightarrow j-1} &= \frac{\exp(\omega_{jm} - E_s \alpha_j)}{1 + \exp(\omega_{jm} - E_s \alpha_j)}, \\ w_{j \rightarrow j} &= \frac{\exp(\omega_{js} - E_s \alpha_j)}{1 + \exp(\omega_{js} - E_s \alpha_j)} - \frac{\exp(\omega_{jm} - E_s \alpha_j)}{1 + \exp(\omega_{jm} - E_s \alpha_j)}, \\ w_{j \rightarrow j+1} &= 1 - \frac{\exp(\omega_{js} - E_s \alpha_j)}{1 + \exp(\omega_{js} - E_s \alpha_j)}, \\ \forall j &\in \{1, 2, \dots, J\} \end{aligned} \quad (5)$$

The model allows learners to make one of three decisions based on their current state  $j$ : upgrade to a higher learning state, remain in the current state, or downgrade to a lower learning state. This decision mechanism ensures the personalization and adaptability of the learning pathway, enabling learners to autonomously choose the most suitable learning state based on their level of knowledge mastery and learning efficiency. However, the model imposes specific restrictions on the range of state transitions; at the lowest learning state  $1$ , learners can only choose to remain in the current state or upgrade, while at the highest learning state  $K$ , learners can only choose to remain in the current state or downgrade. This design ensures the feasibility and continuity of the learning pathway, avoiding leapfrog learning decisions that exceed the learners' capability range.

The model will analyze the learning state at each moment  $t$  through parameter estimation. It integrates all state information up to moment  $t$  and current observational data, using this accumulated information to calculate the probability of the student being in each possible state at moment  $t$ . Then, the model selects the state with the highest probability as the predicted state for that moment, thereby constructing a coherent sequence of states. This approach places more emphasis on the personalization of the learning pathway, considering not just the presentation of course content but including teaching strategies, learning activities, and student feedback, to cater to each student's unique learning needs and preferences. Specifically, assuming the initial state distribution of a student is represented by  $\tau$ , the  $j$ -th column of the student's state transition matrix at moment  $s$  is represented by  $w_{ts-1-j}$ , the probability distribution of personalized learning behaviors for all states at moment  $s$  by  $X_{us}^j$ , and the likelihood function of the student's performance observation  $B_s$  by  $M_s$ . Then, the probability of a learner in PLP  $u$  being in a continuous learning state  $j'$  at moment  $s$  can be calculated as follows:

$$O(c_s = j' / b_1, \dots, b_s) = \tau X_{1j'} \prod_{s=2}^s w_{T_{s-1} \rightarrow j'} X_s^j / M_s \quad (6)$$

In the study of optimizing PLPs, we recognize that students' online learning behaviors do not occur in isolation but are influenced by both the current state  $T_s$  and the transition matrix of the learning pathway  $u$  at moment  $s$ . Here,  $w_{ustb}(a) = O(B_{us}=b | T_{us}=t, W_{us}=w)$  represents the probability of the number of learning resource experiences  $B_{us}$  at moment  $s$  given the student's current state  $t$  and the state transition matrix  $w$ .

The research goal of PLP design features is not only to provide content personalization but also to include personalized management and optimization of state transitions during the learning process, to promote optimal student learning behavior. In this framework, a hierarchical binomial model is used to capture the distribution characteristics of learning behaviors in time series, allowing us to assume that student behavior performance is dependent over time. Assuming the number of attempts to complete a particular teaching activity in learning pathway  $u$  during period  $s$  is represented by  $b_{m'}^s$ , no students fail in the current activity is represented by  $\varepsilon_0$ , and the reaction coefficient under a specific state by  $\varepsilon_{us}$ , the constructed model of learning behavior distribution is as follows:

$$w_{ustb}(a) = \frac{\tilde{b}_{m'}^s}{b_{m'}^s (\tilde{b}_{m'}^s - b)} \eta_{ust}^b (1 - \eta_{ust})^{\tilde{b}_{m'}^s - b}, \quad (7)$$

$$\logus(\eta_{ust}) = \varepsilon_{0us} + \varepsilon_{us}a + \zeta_{1us},$$

To ensure the identifiability of students' online learning behavior states and accurately capture the impact of PLPs on the learning process, we have set some key model constraints and assumptions. First, we assume that the reaction probability of student behavior performance is monotonically increasing across the state sequence, i.e., for all states' indices,  $\varepsilon_{u,j-1} < \varepsilon_{uj}$ ,  $j=2, \dots, v$ , ensuring that the use of online course resources will not decrease as learning states progress. Secondly, at the initial state, we set  $\eta_{us1}=0$ , indicating that at the start of the model, certain factors affecting student learning behavior are fixed or zero. Then, we introduce a random error term  $\zeta_{1us}$ , representing those influences that are unobserved or unmeasurable, assuming it follows a normal distribution.

### III. DYNAMIC PLP RESOURCE RECOMMENDATION BASED ON INCREMENTAL LEARNING

In the field of personalized learning, students' interests and needs change over time, necessitating learning pathway recommendation systems to quickly adapt to these dynamic changes to provide timely and effective resource recommendations. However, traditional static recommendation models cannot effectively address these changes, as they usually assume student preferences are stable [20-24]. At the same time, although existing dynamic recommendation models attempt to capture the evolution of student interests by integrating new information into knowledge graphs, this approach requires full updates of the node embedding vectors in the knowledge graph, which is not only time-consuming but may also reduce the accuracy of recommendations. Fig. 2 provides a schematic diagram of the incremental update of the knowledge graph. To address this challenge, this paper proposes a dynamic PLP resource recommendation model based on incremental learning, which can effectively adapt to changes in students' knowledge states and learning needs. The core advantage of this model is that it updates only the affected parts rather than retraining the entire knowledge graph, significantly reducing model training time and improving the efficiency and accuracy of the recommendation system.

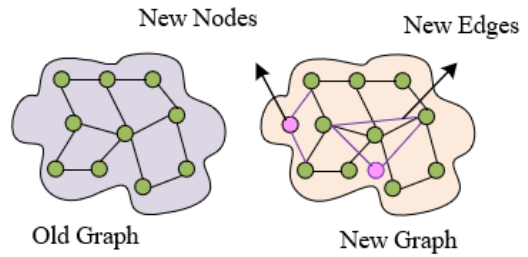


Fig. 2. Schematic diagram of incremental update of the knowledge graph

Specifically, the model first selects key old knowledge nodes from the learning pathway knowledge graph based on the importance of the nodes, then fuses these nodes with new knowledge, initializing embedding vectors for them. Next, through a central node propagation mechanism, the embeddings of these selected nodes are updated to ensure coherence between old and new knowledge. Finally, these updated embeddings are input into an improved graph attention network (such as PNGAT) to generate accurate prediction scores, thereby achieving dynamic recommendation of PLP resources. Compared to traditional dynamic knowledge graph recommendation models, this model is particularly suited for updating and recommending PLPs in educational environments. It not only strengthens the personalized matching of learning resources but also improves the efficiency of model updates through the incremental learning mechanism, thereby better facilitating students' learning development. Fig. 3 shows the structure of the constructed model.

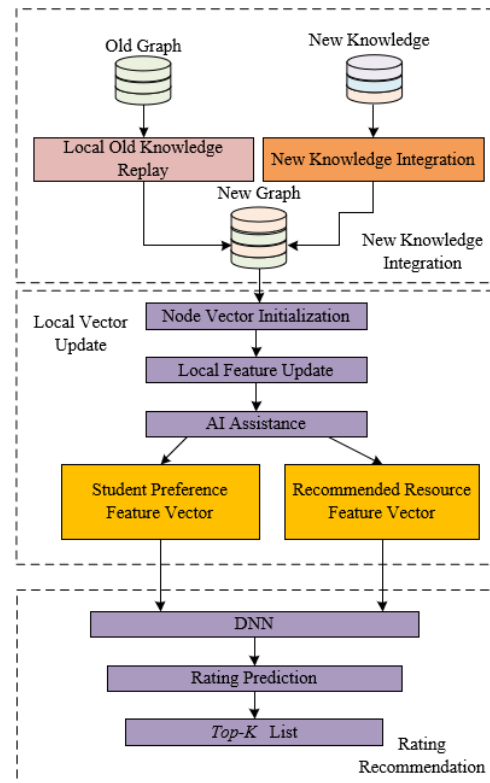


Fig. 3. Structure of the dynamic PLP resource recommendation model based on incremental learning

In the model, we employ an efficient old knowledge sampling strategy to optimize students' learning experiences. This strategy, based on the principle of importance, selects representative and critical old knowledge nodes from the existing learning pathway knowledge graph, which are determined by evaluating their role and performance in students' past learning activities. This ensures that old knowledge is not forgotten when introducing new knowledge and updating learning pathways, while also reducing the computational burden of retraining on the full dataset. For the knowledge graph at the previous moment  $s-1$  represented by  $H_{s-1}$ , and the set of nodes corresponding to student  $i$  and learning resource  $u$  represented by  $X_{s-1}$ , the expression is:

$$X_{s-1} = \{(i, u) | i, u \in H_{s-1}\} \quad (8)$$

A multi-hop information propagation and fusion mechanism can be used to generate students' predictive scores for specific learning resources. Based on this, sampling from students' interaction history can prioritize retaining those old knowledge nodes that interact frequently with students and receive higher predictive scores, reflecting students' learning preferences and needs well. By distinguishing and resampling these old knowledge pieces, the model can not only maintain effective recall of old knowledge when updating learning pathways but also ensure that the personalized recommendation system more accurately captures and reflects students' current learning interests and cognitive states. The proportion of sampling based on student  $i$ 's preference for learning resource  $u$  represented by  $\sigma_{i,u}$ , and the predictive score of student  $i$  for learning resource  $u$  represented by  $h^{i,u}$ , the expression is:

$$\sigma_{i,u} = \frac{\exp(\hat{h}_{i,u})}{\sum_{(i,u) \in X_{s-1}} \exp(\hat{h}_{i,u})} \quad (9)$$

In the model, the key points of local old knowledge sampling focus on how to maintain and update students' learning preferences while ensuring that the recommended learning resources are consistent with students' learning objectives and knowledge backgrounds. Using multi-hop information propagation and fusion technology, it's necessary not only to identify important learning resources from students' interaction history but also to evaluate and extract the most critical parts for students' learning progress and understanding from these resources' associated knowledge points. This involves scoring the importance of entity nodes so that these high-importance knowledge points can be prioritized during the learning pathway update process. The score of learning resource  $u$  for attribute entity node  $r$  represented by  $\hat{h}_{u,r}$  can be calculated through the following formula:

$$\hat{h}_{u,r} = d(u, r | \Phi, H) \quad (10)$$

After obtaining  $\hat{h}_{u,r}$ , the model differentiates and resamples based on the importance of  $r$ . Assuming the proportion of sampling for the rating  $\hat{h}_{u,r}$  of  $u$  for  $r$  is represented by  $\sigma_{u,r}$ , the expression is:

$$\sigma_{u,r} = \frac{\exp(\hat{h}_{u,r})}{\sum_{(u,r) \in X_{s-1}} \exp(\hat{h}_{u,r})} \quad (11)$$

Further assuming the node dataset is represented by  $P_s$  and the daily data sampling ratio is represented by  $\varphi$ , the expression is:

$$\varphi = \frac{|P_s|}{|X_{s-1}|} \quad (12)$$

In the model, the initialization of new knowledge embeddings ensures that as the learning environment continuously evolves, new content, concepts, and learning tasks are timely integrated into the existing learning pathways. The inclusion of new knowledge in this model is not just for maintaining the up-to-date status of the knowledge graph structure but also for providing a personalized learning experience that closely aligns with the students' current learning needs and goals. At moment  $s$ , new learning themes, course resources, or feedback on specific learning content from students may emerge, all considered as the addition of new knowledge nodes and edges. The effective embedding of this new knowledge through incremental learning algorithms needs not only to quickly and accurately locate and update these added nodes in the knowledge graph but also to retain the integrity of the existing knowledge structure without retraining the model comprehensively.

Three potential scenarios for the initialization of new knowledge embeddings in the model can be categorized based on their relevance and source to the existing learning pathways: First, new knowledge might directly emerge within the current knowledge graph  $H_{s-1}$ , often involving a deepening or derivation of concepts that students have already encountered or partially mastered, such as new learning materials or exercises, requiring the recommendation system to integrate these new elements with the students' existing learning pathways; Second, new knowledge might originate from outside the graph  $H_{s-1}$  but be related to its internal knowledge, such as cross-disciplinary new courses or supplementary materials that students may need to expand or reinforce, with the recommendation system needing to identify these knowledge points' potential connections to students' existing pathways and integrate them; Lastly, new knowledge might neither be part of graph  $H_{s-1}$  nor directly related to its internal knowledge, representing entirely new fields or skills to students. In this case, the recommendation system should be able to assess the alignment of these new knowledge points with students' individual learning goals and decide whether to include them as part of the recommendations.

For new knowledge appearing within the knowledge graph  $H_{s-1}$ , the focus is on how to handle the interactions that occur between students and new learning materials and how to update the attributes of related teaching resources. When a student interacts with a new teaching resource, this interaction itself can be considered a new edge, reflecting not only the student's learning progress but also potentially indicating their interest in or need for that field. In the model, it's necessary to update the vector representations of students and teaching



resources to reflect this new interaction. By using an average aggregation algorithm, the embedding vectors of students and newly interacted teaching resources are updated to ensure the personalized recommendation system captures the latest learning states and preferences of students. Assuming the preference embedding vector of student  $i$  at moment  $s$  is represented by  $r_{o,s}$ , the embedding vector of student  $i$  at moment  $s-1$  by  $r_{o,s-1}$ , the set of new associated nodes within graph  $H_{s-1}$  for student  $i$  by  $L_i$ , the number of learning resources  $u$  interacted with by student  $i$  by  $|L_i|$ , and the embedding vector of learning resource  $u$  at moment  $s-1$  by  $r_{n,s-1}$ , the expression is:

$$r_{o,s} = r_{o,s-1} + \frac{1}{|L_i|} \sum_{n \in L_i} r_{n,s-1} \quad (13)$$

In the dynamic PLP resource recommendation model based on incremental learning, for new knowledge appearing outside of the knowledge graph  $H_{s-1}$ , the initialization of new node embedding vectors requires refined handling under different circumstances. For new students or new learning resources related to nodes within the graph, the model averages the embedding vectors of nodes already associated with the new nodes to obtain the initial vector representation of the new nodes. This approach is based on the assumption that new students or new learning resources and their associated existing content have certain feature similarities. Assuming new students from external nodes are represented by  $i_{NE}$  and new learning resources by  $u_{NE}$ , the embedding vector for the new student  $i_{NE}$  obtained through averaging associated node embeddings is represented by  $r_{o,s}$ , the set of nodes within  $H_{s-1}$  associated with  $i_{NE}$  by  $L_i$ , the embedding vector representation associated with learning resource  $i_{NE}$  by  $r$ , and new learning resources associated with nodes within  $H_{s-1}$  represented by  $u_{NE}$ , with the initial embedding vector representation  $r_{u,s}$ , the expression is:

$$r'_{o,s} = \frac{1}{|L_i|} \sum_{n \in L_i} r'_{n,s-1} \quad (14)$$

On the other hand, for new students or new learning resources unrelated to nodes within the graph, lacking direct association information, the model needs to employ a heuristic method, such as selecting a set of nodes with the highest potential relevance to the new node and aggregating their embedding vectors to initialize the new node, possibly considering the distance between nodes as weights to assign a reasonable initial representation to the new node. Assuming new students from external nodes are represented by  $i_{NE}$ , the embedding vector for the new student  $i_{NE}$  unrelated to  $H_{s-1}$  by  $r_{o,s}$ , the distance between new student  $i_{NE}$  and nodes represented by  $\partial_n$ , the set of vectors for the closest nodes within  $H_{s-1}$  represented by  $L_i$ , the embedding vectors for nodes in  $L_i$  by  $r''_{n,s-1}$ , and the embedding vector for new learning resources  $u_{NE}$  unrelated to  $H_{s-1}$  represented by  $r''_{u,s}$ , the expression is:

$$r''_{o,s} = \frac{\partial_n}{\sum_{n \in L_i} \partial_n} \sum_{n \in L_i} r''_{n,s-1} \quad (15)$$

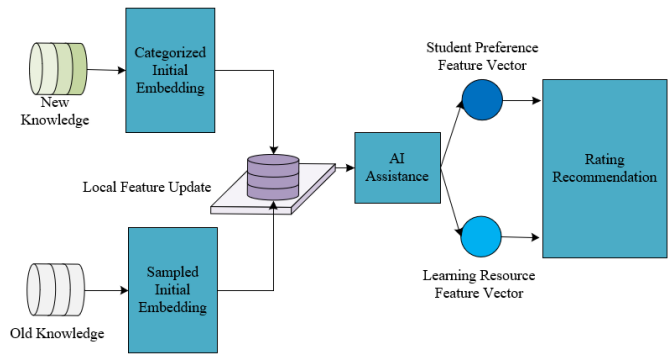


Fig. 4. The process of local embedding update in the model

In the model, local embedding updates employ a central node propagation mechanism to adapt to the integration of new and old knowledge. Specifically, the model first selects old knowledge nodes closely related to the learning pathway using a local sampling strategy based on the principle of importance and reinitializes their embedding vectors to ensure they can represent the state of the knowledge graph  $H_{s-1}$  at moment  $s-1$ . Then, the model integrates node and edge information from new knowledge into the knowledge graph  $H_{s-1}$  to generate new initial embedding vectors. During the process of integrating new and old knowledge, the model needs to update all involved nodes, especially those central nodes connected to both new and old knowledge, as they play a key role in connecting and propagating within the PLP. This update process considers the relationships and mutual influences between nodes to maintain the accuracy and relevance of personalized learning recommendations.

For the local old and new knowledge forming the new graph  $H_s$ , the model adopts a central node-based local embedding update mechanism. Fig. 4 demonstrates the process of local embedding update in the model. When new knowledge is added to the graph, these central nodes propagate their influence to surrounding nodes through the connections in the knowledge graph, triggering a series of node embedding updates. Special attention is paid to the potential overlap in propagation paths among nodes in the knowledge graph, meaning some nodes may receive update signals multiple times due to being on multiple propagation paths. To cater to the optimization needs of students' PLPs, this update strategy reflects not only the addition of new knowledge but also the relevance and update frequency of old knowledge, ensuring each node's embedding vector accurately represents its current position and role in the entire knowledge structure. Specifically, for any node  $n$  on  $H_s$ , its initial embedding vector represented by  $r^{(0)}_{n,s}$ , the first reception of update information from surrounding nodes represented by  $r^{(1)}_{n,s}$ , the set of first-order propagation nodes added for node  $n$  represented by  $\Psi^{(1)}_{n,s}$ , nodes within  $\Psi^{(1)}_{n,s}$  represented by  $n'$ , and the initial embedding vector for added node  $n'$  represented by  $r_{n'}^{(0)}$ . The embedding vectors after the first reception of update information for student preferences and learning resources represented by  $r^{(1)}_{o,s}$  and  $r^{(1)}_{u,s}$ , respectively, the expression is:

$$r_{n,s}^{(1)} = r_{n,s}^{(0)} + \frac{1}{|\Psi_{n,s}^{(1)}|} \sum_{n' \in \Psi_{n,s}^{(1)}} r_{n'}^{(0)} \quad (16)$$

Assuming node  $n$  has been updated  $v-1$  times with the corresponding embedding vector represented by  $r^{(v-1)}_{n,s}$ , its  $v$ -th update is represented by  $r^{(v)}_{n,s}$ . Further assuming the set of  $g-1$ -th order propagation nodes added for node  $n$  represented by  $\Psi^{(g-1)}_{n,s}$ , nodes within  $\Psi^{(g-1)}_{n,s}$  represented by  $n'$ , and the embedding vectors after the  $v$ -th reception of update information for student preferences and learning resources represented by  $r^{(n)}_{o,s}$  and  $r^{(n)}_{u,s}$ , the expression is:

$$r^{(v)}_{n,s} = r^{(v-1)}_{n,s} + \frac{1}{|\Psi^{(g-1)}_{n,s}|} \sum_{n' \in \Psi^{(g-1)}_{n,s}} (r_{n'}^{(j-1)} - r_{n'}^{(j-2)}) \quad (17)$$

Finally, by inputting the feature vectors of student preferences and learning resources into a  $DNN$ , it outputs  $h^{i,u,s}$ , providing a PLP resource  $Top-K$  recommendation list.

#### IV. EXPERIMENTAL RESULTS AND DISCUSSION

In conducting relevant experiments, this paper utilized various types of datasets. We used online education platform data, sourced from MOOC platforms, K-12 education platforms, university internal learning management systems, etc. The basic attributes include: 1) student behavior data such as video watching time, course completion status, assignment submission records, and exam scores; 2) interaction data such as student posts in discussion forums, question-and-answer activities, likes, and comments; 3) metadata such as course content, instructor information, course structure, and outlines. This paper also utilized teaching system log data, sourced from internal school teaching systems, virtual learning environments, etc. The basic attributes include: 1) student login records such as login time, duration, and frequency; 2) system usage data such as the frequency and duration of accessing different modules; 3) interaction records such as the number and content of student interactions with teachers or classmates. Additionally, this paper used personalized questionnaire and survey data, which came from student feedback questionnaires on PLPs, satisfaction surveys, etc.

According to the PLP resource access shown in Table I, there are significant differences in the access number and average access time among different types of learning resources. Interactive exercises and e-books and reading materials have the highest access numbers, 256 and 286 times respectively, indicating these resources are highly attractive and frequently used in students' learning processes. Simulators and virtual labs, though accessed less frequently (14 times), have the longest average access time (278 seconds), suggesting they may involve more complex and in-depth learning activities. In contrast, discussion forums and communities, as well as educational games and simulations, have very low access numbers (3 and 6 times, respectively) and short access times, possibly indicating that these resources are not closely related to students' needs in the current learning pathway design or may not be prominent in students' learning processes.

TABLE I. PLP RESOURCE ACCESS

Resource Type	Access Number	Average Access Time(s)
Video Lectures	107	121
Interactive Exercises	256	158
E-books and Reading Materials	286	121
Discussion Forums and Communities	3	5
Discussion Forums and Communities	139	124
Simulators and Virtual Labs	14	278
Educational Games and Simulations	6	129

From the data table provided in Fig. 5, one can observe the unique trends in the impact of different types of recommended resources on the learning process as the personalized learning activity number increases. Recommended resource 1 in the graph represents foundational knowledge resources, recommended resource 2 represents application and problem-solving resources, recommended resource 3 represents challenging and extension resources, recommended resource 4 represents feedback and correction resources, and recommended resource 5 represents collaborative learning and social resources. It can be seen that the impact value of recommended resource 1 (foundational knowledge resources) slowly increases from 0.26 at activity 0 to 0.2618 at activity 19, showing a consistently stable growth, reflecting the continuous positive impact of foundational knowledge resources on the learning process. The impact values of recommended resources 2 (application and problem-solving resources) and 3 (challenging and extension resources) also show a gradual increase, though the growth is modest, indicating the gradually strengthening effect of these resources on deepening understanding and skill application. In contrast, the impact values of recommended resources 4 (feedback and correction resources) and 5 (collaborative learning and social resources) start high but then decrease, which might indicate these resources are more helpful at the beginning of learning, but their influence decreases as students' abilities improve. Compared to the uniform baseline of 0.26 without resource impact, all recommended resources' impact values have increased, demonstrating the positive effect of resource introduction on the learning process.

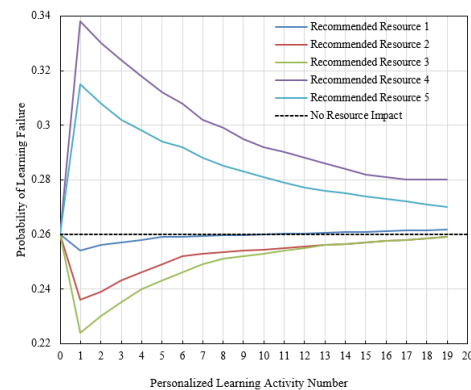


Fig. 5. The impact of long-term variables in different PLP resources on the learning process

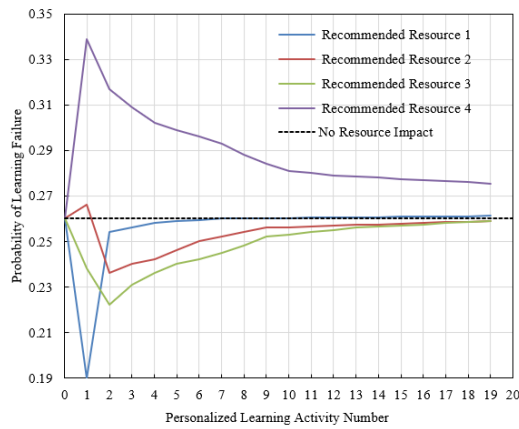


Fig. 6. Impact of different PLP resources on the learning process considering both long-term and immediate effects

From the data table given in Fig. 6, diverse trends can be observed in the impact of different types of PLP resources on the student learning process. Foundational knowledge resources (Recommended Resource 1) gradually decrease from an initial value of 0.26 at activity number 0 to 0.19 at activity number 1, then slowly rise until reaching 0.2612 at activity number 19, showing a trend of initial decline followed by an increase. This suggests that the mastery of foundational knowledge may be initially hindered due to difficulty or students' adaptation issues but shows a gradually positive impact on the learning process as the study progresses. Application and problem-solving resources (Recommended Resource 2) and challenging and extension resources (Recommended Resource 3) both start at 0.26 from activity number 0 and then show a declining trend before gradually increasing. This may reflect that these resources could initially be too complex for students, leading to a decrease in learning effectiveness, but their positive effects gradually strengthen as students' capabilities improve. Feedback and correction resources (Recommended Resource 4) start with the highest impact value of 0.339, then show a significant declining trend, dropping to 0.2755 by activity number 19, suggesting these types of resources are very effective in correcting mistakes and guiding learning directions at the beginning of study but reliance on these resources may gradually reduce as students progress in their learning.

The data from Fig. 5 and 6 reveals that the constructed dynamic model can uncover the immediate and long-term impacts of different PLP resources over time. The model shows that foundational knowledge resources have a relatively stable long-term positive impact on learning, while the effects of application and problem-solving resources, as well as challenging and extension resources, gradually emerge after an initial adaptation phase, reflecting their growing importance in the learning process. Feedback and correction resources provide crucial support early on but their impact diminishes as students improve their self-regulation capabilities. These

results underscore the importance of PLP design features, indicating that the dynamic model can effectively capture the dynamic impacts of different resource types, providing robust data support for real-time adjustment of learning resources and optimization of learning pathways.

Recall measures the proportion of positive instances that are correctly identified by the classifier among all positive instances. A higher recall indicates that the classifier is better at identifying positive instances, while a lower recall suggests that the classifier may have missed some positive instances. The state transition matrices listed in Table II give the probability impact of different PLP resource factors on student learning state transitions. Taking Recommended Resource 1 as an example, the probability for students transitioning from state 1 to state 1 is very high (0.921), indicating foundational knowledge resources help students maintain their learning state and prevent regression. The matrices for Recommended Resources 2 and 3 show that although these resources maintain a high probability for students to stay in state 1 (Resource 2 at 0.978, Resource 3 at 0.952), the probability of transitioning from state 2 back to state 1 is relatively low (Resource 2 at 0.289, Resource 3 at 0.378), suggesting these resources make it less likely for students who have acquired some application ability or challenging knowledge to return to foundational knowledge states. Recommended Resource 4 shows a unique pattern for state 2 transitions, with a very high probability of transitioning to state 3 (0.214), indicating feedback and correction resources are effective in pushing students from applied knowledge to higher learning states. The matrix for Recommended Resource 5 displays a higher probability of transitioning from state 1 to state 2 (0.415), and a relatively high probability from state 3 to state 2 (0.127), suggesting collaborative learning and social resources might facilitate students transitioning from foundational to applied knowledge, and also help advanced learners consolidate their application knowledge.

The analysis of these state transition matrices emphasizes the effectiveness of the constructed dynamic model for PLP design features. By accurately depicting the specific impact of different resource types on student learning state transitions, the model provides deep insights into the student learning process, enabling educators to dynamically adjust teaching resources based on students' current learning states and progress. For instance, foundational knowledge resources help maintain stability within the same state, feedback and correction resources are particularly effective for transitioning to advanced states, and collaborative learning resources facilitate transitions between different states. This model not only shows how PLP resources can facilitate transitions from one state to another but also guides educators on how to design targeted and flexible teaching strategies that align with students' individual learning needs, thereby optimizing student learning outcomes.



TABLE II. IMPACT OF PLP RESOURCE FACTORS ON STUDENT LEARNING PROCESS STATE TRANSITIONS

State Transition Matrix for Recommended Resource 1		State 1	State 2	State 3
	State 1	0.921	0.082	0.000
	State 2	0.178	0.789	0.018
	State 3	0.000	0.018	0.987
State Transition Matrix for Recommended Resource 2		State 1	State 2	State 3
	State 1	0.978	0.026	0.000
	State 2	0.289	0.689	0.009
	State 3	0.000	0.009	0.987
State Transition Matrix for Recommended Resource 3		State 1	State 2	State 3
	State 1	0.952	0.032	0.000
	State 2	0.378	0.625	0.006
	State 3	0.000	0.011	0.978
State Transition Matrix for Recommended Resource 4		State 1	State 2	State 3
	State 1	0.956	0.035	0.000
	State 2	0.014	0.789	0.214
	State 3	0.000	0.006	0.989
State Transition Matrix for Recommended Resource 5		State 1	State 2	State 3
	State 1	0.589	0.415	0.000
	State 2	0.031	0.845	0.121
	State 3	0.000	0.127	0.887

TABLE III. EXPERIMENTAL RESULTS OF DIFFERENT DYNAMIC PLP RESOURCE RECOMMENDATION METHODS ON DIFFERENT DATASETS

Dataset	Method	Recall1	Recall2	Recall3	Average	%Imp	Time
Online Education Platform Dataset	LSTM	0.689	0.689	0.674	0.689	-	1.3h
	GAT	0.735	0.732	0.732	0.732	7.4%	0.6h
	DeepCF	0.754	0.745	0.745	0.745	9.1%	1.1h
	ICFNN	0.789	0.774	0.756	0.784	11.5%	1.2h
	The proposed method	0.845	0.875	0.879	0.851	23.6%	5.4h
Learning Management System Dataset	LSTM	0.721	0.732	0.721	0.723	-	2.2h
	GAT	0.759	0.756	0.754	0.751	4.6%	0.5h
	DeepCF	0.789	0.761	0.774	0.783	6.8%	1.3h
	ICFNN	0.789	0.778	0.787	0.789	8.7%	2.2h
	The proposed method	0.912	0.897	0.912	0.915	22.5%	9.2h

In two different datasets - "Online Education Platform Dataset" and "Learning Management System Dataset," several dynamic PLP resource recommendation algorithms were compared. *Recall1*, *Recall2*, and *Recall3* in the table represent the model's *Recall@20* after adding different volumes of data as new data. From Table III, it is evident that the incremental learning-based method proposed in this paper outperforms other methods across all metrics. For the Online Education Platform Dataset, the method's *Recall1*, *Recall2*, and *Recall3* are 0.845, 0.875, and 0.879, respectively, with an average recall (*Average*) reaching 0.851, a 23.6% improvement over the baseline model (*LSTM*). In the Learning Management System Dataset, the method also significantly outperforms other methods, with an average recall of 0.915, which is a 22.5% improvement compared to the LSTM baseline model. Although the method takes relatively longer computation times (5.4 hours and 9.2 hours, respectively), the significant improvements in recommendation accuracy demonstrate its effectiveness.

These experimental results clearly show that the incremental learning-based dynamic PLP resource recommendation algorithm proposed in this paper is not only capable of handling real-time data to adapt to learners' constantly changing needs but also significantly improves recommendation accuracy compared to other methods. The high recall rates indicate that the method can more accurately predict the learning resources learners are likely to choose or prefer, which is extremely important for providing

personalized learning experiences. Although the algorithm sacrifices time efficiency, accuracy is more critical in educational applications since it directly affects learning outcomes and learner satisfaction.

As shown in Fig. 7 below, in both datasets, as feature dimensions increase from 16 to a maximum of 256, *Recall@20* values first show an upward trend, peaking at 34 dimensions, with *Recall@20* for Dataset 1 and Dataset 2 reaching 0.776 and 0.788, respectively. Afterwards, as feature dimensions continue to increase to 120 and 256, *Recall@20* decreases, indicating that increasing feature dimensions beyond a certain point does not significantly help improve the model's predictive performance and may even lead to model overfitting due to excessive dimensionality. Regarding computation time, as feature dimensions grow, model training time significantly increases. In Dataset 1, training time grows from 0.6 hours to 3.55 hours as feature dimensions increase from 16 to 256; in Dataset 2, it grows from 1.05 hours to 4.8 hours. This indicates that higher feature dimensions lead to increased model complexity and computational costs.

It can be concluded that feature dimensions have a direct impact on the performance of the incremental learning-based dynamic PLP resource recommendation algorithm. The proper selection of feature dimensions is crucial for optimizing the algorithm's performance. Too low dimensions may not capture the characteristics of the data fully, while too high dimensions may cause overfitting and increase computational burden. In this paper, a feature dimension of 34 is identified as the optimal

dimension for *Recall@20* performance in both datasets, indicating that the algorithm can achieve high accuracy in recommendations without excessively increasing computational complexity.

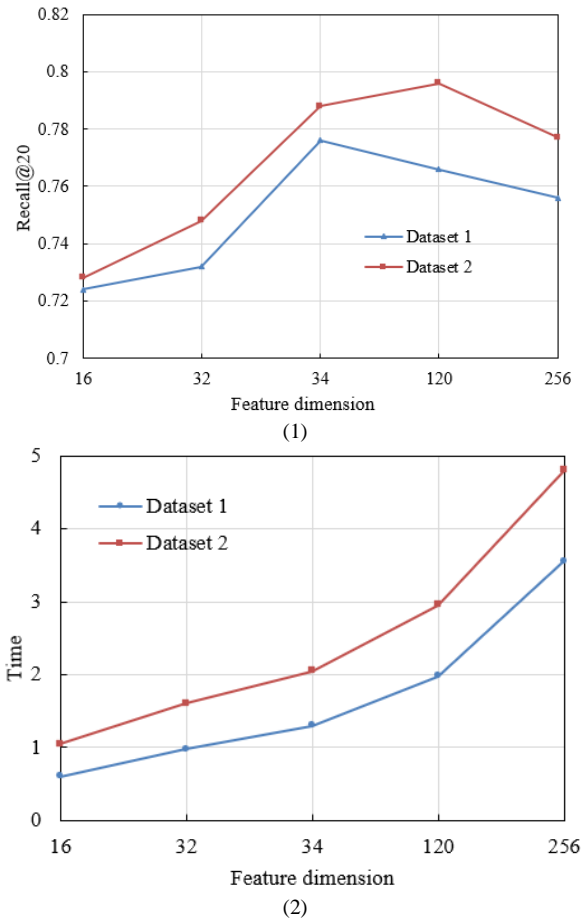


Fig. 7. The impact of feature dimensions on Recall@20 and time in different datasets

As shown in Fig. 8 below, in both datasets, *Recall@20* values generally show an increasing trend with the rise in central node propagation orders. For Dataset 1, as the central node propagation order increases from 0 to 3, *Recall@20* rises from 0.52 to 0.775, then slightly decreases to 0.765 at order 4. Similarly, in Dataset 2, *Recall@20* increases from 0.58 to 0.785, peaking at order 3, and then decreases to 0.74 as the order increases to 4. This suggests that there is an optimal propagation order, and excessive propagation orders do not continue to improve the accuracy of recommendations, possibly due to information over-spreading leading to the introduction of noise. Regarding time consumption, processing time in both datasets increases with the rise in propagation orders, from 0.4 hours to 2.2 hours in Dataset 1, and from 0.7 hours to 3.6 hours in Dataset 2, indicating the algorithm's time complexity increases with the number of propagation orders.

The incremental learning-based dynamic PLP resource recommendation algorithm proposed in this paper has shown promising results in the experiments. By adjusting the central node propagation orders, the algorithm can control the breadth and depth of information spread to a certain extent, thereby

more accurately simulating learners' learning pathways and preferences. Experimental data show that at propagation order 3, the algorithm achieves the best *Recall@20* performance on both datasets, indicating the algorithm reaches the best balance between recommendation accuracy and computational efficiency at this order. Although the recommendation algorithm's time cost increases with the propagation orders, considering the high demand for recommendation accuracy in online education platforms and learning management systems, this time investment is reasonable.

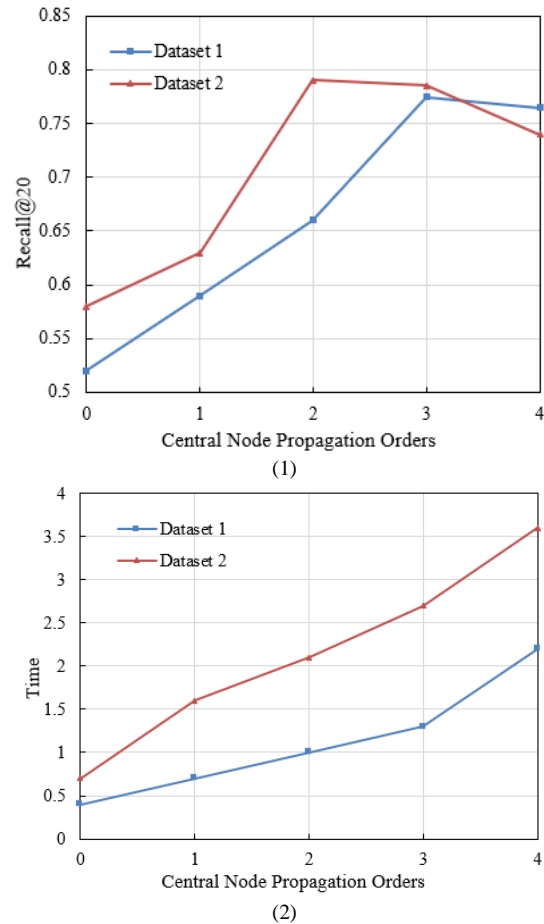


Fig. 8. The impact of central node propagation orders on Recall@20 and time in different datasets

The paper verifies the effectiveness of the proposed dynamic PLP resource recommendation algorithm based on incremental learning through experiments. In the experiments, researchers used datasets from different sources, mainly including data from online education platforms and learning management systems. These datasets provided rich student learning behavior data and background information, allowing the algorithm to be validated in diverse learning environments. The experimental results show that as the number of propagation steps of the central node increases, the accuracy (*Recall@20*) of personalized resource recommendations significantly improves, eventually reaching a peak. This indicates that the algorithm can effectively capture students' learning needs and behavior patterns in the early stages, thereby improving the accuracy of recommendations.

However, when the number of propagation steps continues to increase, the accuracy begins to decline slightly. This phenomenon may be due to information overload or increased noise caused by excessive propagation steps, affecting the recommendation performance. This trend is reflected across different datasets, demonstrating the algorithm's consistency and stability in different learning environments. Through experiments, the researchers further examined the impact of different PLP resource factors on student learning state transitions. Specifically, they analyzed how different resource recommendation strategies influence students' learning progress and knowledge mastery. The experimental results show that the diversity and adaptability of recommended content play a crucial role in the transition of students' learning states. Regarding the impact of feature dimensions on recommendation efficiency and time cost, the experimental results provide valuable insights. While increasing feature dimensions can enhance the accuracy of the recommendation algorithm, it also significantly increases computation time and resource consumption. The paper quantifies this trade-off relationship through experimental data, pointing out that in practical applications, a balance needs to be struck between recommendation accuracy and computational efficiency to ensure system usability and responsiveness.

## V. CONCLUSION

The core contribution of this paper lies in constructing a dynamic model to simulate and analyze the impact of PLP on the student learning process. Based on real-time learning data of students, this model captures changes in students' learning states and needs, providing reliable theoretical support for the design of PLP. Furthermore, the paper proposes an incremental learning-based dynamic PLP resource recommendation algorithm that can adjust recommendation strategies in real-time to ensure that recommended content remains consistent with students' immediate learning states. This algorithm not only focuses on the short-term effectiveness of recommendations but also considers the role of long-term variables in learning pathway design and how these variables affect the long-term transformation of student learning states.

Experimental results indicate that the algorithm proposed in this paper improves personalized resource recommendation accuracy (Recall@20) with the increase of central node propagation orders, reaching a peak before slightly declining. This trend is consistent across different datasets (Online Education Platform and Learning Management System). The experiments also examine the impact of different PLP resource factors on student learning state transitions and the effect of feature dimensions on recommendation efficiency and time cost, providing a comprehensive analysis perspective.

This paper's approach provides a new perspective and technical means for the application of AI in the field of education. The combination of dynamic models and incremental learning algorithms can not only be applied to the optimization of PLPs but can also be extended to other intelligent systems that require real-time feedback and dynamic adjustments, having broad application prospects. Through a comprehensive analytical perspective, the paper integrates theoretical models with practical applications, providing a

comprehensive understanding of PLP design and resource recommendation. Theoretically, the paper provides a reliable theoretical foundation for the design of PLPs, clarifying the application value of dynamic models and incremental learning algorithms in educational technology. From a practical standpoint, through detailed experimental analysis, the paper provides practical guidance for the development and optimization of educational technology systems, including how to apply the proposed algorithm in different learning environments and how to balance recommendation effectiveness and computational efficiency. However, the research has limitations, such as the increased time cost, which may affect the algorithm's feasibility and scalability in resource-limited environments. Future research directions could include optimizing the algorithm to reduce computational resource consumption, exploring the impact of more long-term variables on the learning process, and validating the model's generalizability in different educational settings. Furthermore, the research could further consider the interaction between PLP design and students' psychological states and learning motivations to support more comprehensive educational interventions.

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