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Multi-Objective Optimization for Personalized Educational Pathway Planning: A Temporal Student Modeling Approach

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ABSTRACT: Personalized educational pathway planning requires learning systems to continuously adapt instructional sequences to the evolving knowledge, behaviour, learning objectives, and cognitive characteristics of individual students. Conventional recommendation approaches frequently rely on static learner profiles or optimize a single criterion, limiting their ability to accommodate changes in student knowledge and competing educational requirements. This paper proposes a temporal student modeling approach for multi-objective optimization of personalized educational pathways. The proposed framework models learner knowledge as a dynamically evolving state derived from sequential assessments, learning-resource interactions, progression history, engagement patterns, and temporal behaviour. A multi-objective optimization layer subsequently generates feasible learning pathways by simultaneously considering knowledge mastery, learning efficiency, knowledge coverage, cognitive difficulty, learner engagement, and prerequisite consistency. Rather than producing an immutable sequence, the framework continuously updates and re-optimizes the remaining pathway as new evidence regarding student performance becomes available. The approach integrates temporal knowledge tracing, educational dependency modeling, and Pareto-based pathway optimization into a unified framework. The proposed formulation provides a foundation for adaptive and learner-centered educational systems capable of balancing short-term learning requirements with long-term educational goals while maintaining pedagogical coherence and pathway flexibility.

1. INTRODUCTION

The rapid expansion of intelligent educational technologies, learning management systems, massive open online courses, and data-driven instructional platforms has created new opportunities for delivering learning experiences that are adapted to individual students. Unlike conventional instructional environments in which learners are generally exposed to a common curriculum sequence, contemporary digital learning environments can continuously collect information regarding assessment responses, learning-resource consumption, interaction frequency, completion behaviour, time expenditure, repeated attempts, and progression through conceptual units. These data provide the foundation for personalized educational pathway planning, in which the sequence of learning activities is determined according to the learner's knowledge, learning objectives, capabilities, and observed behaviour. Personalized learning-path recommendation has consequently become an important research problem within educational data mining, recommender systems, artificial intelligence, and learning analytics [3], [4].

A personalized educational pathway differs fundamentally from conventional educational-resource recommendation. A recommendation system may identify a resource that is relevant to a learner, whereas pathway planning must determine an

ordered and pedagogically coherent sequence of resources. The sequence must account for prerequisite relationships, conceptual dependencies, learning objectives, resource difficulty, expected learning gain, and the learner's current level of mastery. A resource that appears highly relevant in isolation may be inappropriate if the learner has not acquired its prerequisite knowledge. Similarly, repeatedly recommending resources that have already been mastered can increase learning time without providing proportional educational benefit. Consequently, personalized pathway planning requires an integrated representation of both the learner's evolving state and the structural relationships among educational resources [4], [5].

One of the central challenges in this area is that student knowledge is inherently dynamic. Learners continuously acquire, consolidate, forget, revise, and apply knowledge as they interact with educational materials. Therefore, a student profile generated at the beginning of a course cannot necessarily represent the learner's state several sessions later. Knowledge tracing was developed precisely to estimate the evolution of learner knowledge from sequences of educational interactions. Deep Knowledge Tracing demonstrated that recurrent neural architectures could model latent student knowledge from historical response sequences, establishing a major transition from static learner profiling toward sequential learner-state estimation [10]. Subsequently, Dynamic Key-Value Memory Networks explicitly represented knowledge concepts and dynamically updated their associated mastery states, providing a more structured representation of changing learner knowledge [9].

The temporal nature of student modeling is particularly important for pathway planning because the appropriate next learning activity depends on the learner's **current state rather than only historical performance**. For example, two students may have the same cumulative assessment score while possessing substantially different mastery profiles. One learner may have recently mastered foundational concepts and therefore be ready for advanced material, whereas another may have achieved the same aggregate score through strong performance in some concepts while retaining significant deficiencies in prerequisites. A pathway planner that uses only aggregate performance would fail to distinguish these situations. Temporal student modeling enables the system to represent such differences and use them when selecting subsequent learning activities [7], [9].

Recent research has increasingly attempted to connect temporal knowledge tracing with personalized learning-path generation. Zhang, Feng, and Wang demonstrated that process mining combined with deep knowledge tracing can generate learning pathways containing sequential, parallel, and alternative relationships between learning objects, while dynamically selecting branches according to the learner's knowledge state [5]. Their findings address an important limitation of conventional global pathway recommendation, in which a complete sequence is generated before learning and may become inappropriate when the learner's knowledge changes during pathway execution. The process-oriented formulation therefore demonstrates the importance of maintaining pathway flexibility while simultaneously responding to evolving student knowledge [5].

Another important development is the incorporation of cognitive characteristics into pathway generation. Tong and Ren proposed an architecture integrating deep knowledge tracing with cognitive-load estimation, allowing learning trajectories to account not only for estimated knowledge but also for the cognitive demands imposed by learning activities [2]. Similarly, Wei et al. incorporated educational-psychology principles into personalized pathway generation by combining decay-aware knowledge tracing, candidate-space optimization, and multiple constraints governing the matching between learner knowledge and educational content [3]. These studies indicate that effective personalization should consider more than predictive accuracy and should account for the cognitive and pedagogical characteristics of the learning process.

Despite these advances, educational pathway planning remains a fundamentally **multi-objective optimization problem**. A useful learning pathway should increase knowledge mastery while also maintaining reasonable learning duration, sufficient conceptual coverage, appropriate cognitive difficulty, learner engagement, and prerequisite consistency. These objectives can conflict. For example, maximizing knowledge coverage may require a longer pathway, whereas minimizing learning time may result in insufficient reinforcement. Increasing content difficulty may be beneficial for an advanced learner but counterproductive for a learner with weak prerequisite knowledge. Maximizing engagement may also lead to preference for familiar content rather than the content most necessary for achieving the learner's educational objective.

The use of a single optimization criterion is therefore inadequate for representing the complexity of personalized educational planning. A pathway that maximizes immediate predicted assessment performance may not minimize total learning time. Similarly, a pathway that minimizes duration may not maximize long-term mastery. Multi-objective optimization addresses this issue by considering several competing objectives simultaneously and identifying a set of non-dominated solutions. The resulting Pareto-optimal pathways provide alternative trade-offs between learning effectiveness, efficiency, cognitive demand, engagement, and coverage rather than forcing all learners into one predetermined optimization strategy.

Recent research provides direct evidence for this direction. Contemporary learning-path systems have begun combining knowledge tracing with deep reinforcement learning and multi-objective curriculum planning to address the temporal and competing requirements of personalized education [1]. Such approaches recognize that pathway planning can be treated as a sequential decision problem in which the learner's state evolves after every learning interaction and the instructional system must repeatedly determine an appropriate action. This formulation is substantially closer to the actual learning process than static recommendation.

The temporal dimension also introduces an important distinction between **pathway generation** and **pathway execution**. In static systems, a complete pathway may be generated once and subsequently followed without substantial modification. In a temporal system, the pathway is continuously reconsidered as evidence about the learner becomes available. If a learner demonstrates unexpectedly high mastery, unnecessary remedial resources can be removed and more advanced resources can be introduced. Conversely, if a learner performs below the predicted level, prerequisite reinforcement or additional practice can be inserted. Thus, personalization becomes a closed-loop process consisting of student-state estimation, pathway optimization, learning activity execution, observation, and subsequent state updating [1], [5].

The research problem addressed in this paper is consequently the development of a **multi-objective optimization framework for personalized educational pathway planning based on temporal student modeling**. The proposed approach considers the learner as a dynamic state rather than a static profile and integrates sequential student evidence with educational-resource relationships. The pathway planner is designed to optimize multiple educational objectives simultaneously while respecting prerequisite and pedagogical constraints.

The principal contribution of the proposed research lies in establishing an integrated framework linking three traditionally distinct components: temporal student modeling, educational pathway representation, and multi-objective optimization. The temporal modeling component estimates evolving knowledge and behavioural states; the educational representation component captures relationships among concepts, resources, prerequisites, and learning objectives; and the optimization component identifies pathways that provide appropriate trade-offs among mastery, efficiency, coverage, cognitive demand, and engagement. The framework further supports continuous pathway re-optimization as new student evidence becomes available.

Accordingly, the study moves beyond the conventional question of *which learning resource should be recommended next* toward the broader question of *which sequence of educational activities should be selected for this learner at this point in time, given the learner's evolving state and multiple competing educational objectives*. This formulation provides a foundation for adaptive educational systems capable of generating flexible, learner-specific, and continuously evolving educational pathways.

2. LITERATURE REVIEW

2.1 Personalized Learning and Educational Pathway Recommendation

Personalized learning aims to adapt educational experiences according to individual differences in prior knowledge, learning ability, objectives, preferences, and behaviour. In digital educational environments, this personalization increasingly relies on computational models capable of processing large volumes of learner interaction data. Learning-path recommendation represents a more advanced form of personalization because it determines not merely the relevance of individual resources but the sequence in which multiple learning activities should be completed [4], [5].

Existing pathway recommendation approaches can broadly be distinguished into **global pathway generation** and **local iterative recommendation**. Global approaches construct an entire pathway according to the learner's initial state and target objective. Their principal advantage is that learners can obtain an overview of the intended educational trajectory. However, such a pathway can become inappropriate if the learner's knowledge changes substantially during execution. Local iterative approaches instead select the next learning object according to the learner's most recent state, allowing greater adaptation but potentially providing limited visibility of the overall pathway structure [5].

The tension between these two approaches is particularly relevant to personalized pathway planning. A completely fixed pathway sacrifices adaptability, whereas an entirely local recommendation mechanism may sacrifice long-term planning. Zhang et al. addressed this issue through a process-type learning pathway that represents sequences, parallel relationships, and alternative branches while using deep knowledge tracing and decision mining to select appropriate branches according to learner knowledge [5]. This demonstrates that pathway personalization can benefit from a combination of global structural planning and local state-dependent adaptation.

2.2 Student Modeling and Knowledge Tracing

Student modeling provides the computational representation of learner characteristics required by adaptive educational systems. Among different student-modeling techniques, knowledge tracing has received substantial attention because it attempts to estimate latent knowledge states from observed learning interactions. Traditional knowledge tracing models generally estimate the probability that a learner has mastered a particular knowledge component based on previous responses.

Deep Knowledge Tracing significantly expanded this research direction by using recurrent neural networks to learn latent representations of student knowledge from sequential interactions [10]. The model demonstrated that learner performance could be predicted by learning temporal patterns directly from historical assessment sequences. This was important because student knowledge is not independent across time; previous learning activities influence subsequent performance.

Dynamic Key-Value Memory Networks subsequently introduced a structured memory representation in which one memory component represents knowledge concepts while another dynamically represents their corresponding mastery levels [9]. This architecture provided a more explicit relationship between concepts and evolving student mastery. The approach is particularly relevant to personalized pathway planning because identifying the learner's mastery of individual concepts is necessary for determining whether prerequisite conditions for subsequent resources have been satisfied.

A comprehensive survey of knowledge tracing research further demonstrates the progression from probabilistic approaches to deep learning, memory-augmented architectures, attention mechanisms, graph-based approaches, and other advanced sequential models [7]. These developments establish temporal student modeling as a mature methodological foundation for adaptive educational applications. However, knowledge tracing primarily addresses **state estimation and prediction**. It does not, by itself, determine the optimal sequence of instructional resources when several educational objectives must be satisfied simultaneously.

2.3 Temporal Modeling of Learning Behaviour

Temporal modeling extends knowledge tracing by considering not only the sequence of responses but also the temporal characteristics of learning behaviour. Time between interactions, repetition, recency, learning frequency, progression speed, and changes in performance can provide important information about the learner's current state.

The importance of temporal information is particularly evident when historical performance is used to predict future learning. A learner's performance on a concept several weeks earlier may have less predictive value than a recent assessment involving the same concept. Similarly, repeated unsuccessful attempts within a short period may indicate a persistent difficulty that should influence pathway selection.

Recent personalized learning-path research has incorporated temporal or sequential information directly into pathway construction. Zhang et al. used deep knowledge tracing to annotate learner knowledge states from historical learning logs and then combined those states with process mining to construct flexible pathway structures [5]. This approach demonstrates that learner history can serve not only as a prediction input but also as a decision variable for determining alternative pathway branches.

The temporal perspective also changes the interpretation of personalization. A learner should not be considered permanently "advanced," "intermediate," or "weak." Instead, different knowledge components may evolve at different rates. A student can simultaneously possess high mastery of one concept and low mastery of another. Consequently, personalized pathways should be conditioned on a time-dependent, concept-specific state rather than a single overall proficiency label.

2.4 Cognitive Load and Educational Psychology in Pathway Generation

Knowledge mastery alone does not provide a complete representation of the learning process. The cognitive demand associated with a resource can influence whether the learner can effectively process and retain its content. Excessive difficulty may produce failure and disengagement, while insufficient difficulty may lead to inefficient learning and limited progression.

Tong and Ren integrated deep knowledge tracing with cognitive-load estimation in a dual-stream neural architecture for personalized learning-path generation [2]. Their approach demonstrates the value of combining learner knowledge estimation with cognitive characteristics when constructing learning trajectories. Instead of treating every learning object as an equivalent candidate, the system considers whether the learner is cognitively prepared for the content.

Wei et al. similarly incorporated educational psychology into personalized learning-path generation, using decay-aware knowledge tracing, candidate-space optimization, and multiple constraints to align learning content with the learner's knowledge state [3]. Their findings reinforce the argument that pathway planning should incorporate pedagogical principles rather than rely solely on statistical similarity between learners and resources.

These studies are particularly relevant to a multi-objective framework because cognitive load can be treated as one objective among several. The system may seek to maximize expected learning gain while simultaneously minimizing excessive cognitive burden. This creates a more realistic representation of instructional planning than optimizing assessment performance alone.

2.5 Knowledge Graphs and Structured Learning Pathways

Knowledge graphs provide a mechanism for representing relationships among educational concepts, resources, learning objectives, and prerequisites. In a pathway-planning context, such relationships can be used to constrain the search space and ensure that recommended sequences maintain pedagogical consistency.

A knowledge graph can represent a prerequisite relationship in which mastery of concept $A$is required before concept B. It can also represent semantic relationships between related concepts, resource-to-concept associations, alternative resources, and hierarchical relationships. Such representations allow pathway-planning systems to move beyond purely statistical recommendations toward structurally constrained educational planning.

However, a static knowledge graph does not automatically capture the changing state of the learner. The graph may remain unchanged while the learner moves from low to high mastery of its constituent concepts. Therefore, effective personalization requires the combination of a relatively stable educational structure with a dynamic learner-state representation.

Recent research has increasingly addressed this integration by combining knowledge graphs with knowledge tracing and sequential decision models [1], [5]. The emerging direction is particularly important for multi-objective pathway planning because the knowledge graph can provide the **feasible solution space**, while the temporal student model determines which portions of that space are appropriate for the current learner.

The 2026 work on joint optimization of deep reinforcement learning and knowledge tracing provides a particularly relevant development. Its framework explicitly combines temporal-aware graph knowledge tracing with a multi-objective curriculum planner, addressing knowledge-state dynamics together with competing objectives such as knowledge consolidation, exploration, and cognitive-load management [1]. This indicates a clear movement in the field toward integrated temporal and multi-objective pathway planning.

2.6 Multi-Objective Optimization and Research Gap

Educational pathway planning involves multiple objectives that cannot always be optimized simultaneously. Knowledge mastery, learning efficiency, coverage, engagement, cognitive suitability, and prerequisite consistency may point toward different pathways. Consequently, selecting a single pathway based on one objective can result in solutions that are optimal from one perspective but inefficient or pedagogically unsuitable from another.

Multi-objective optimization provides a suitable framework because it searches for non-dominated pathways rather than assuming that a single universal optimum exists. A Pareto-based approach can identify several pathways representing different trade-offs. For example, one pathway may maximize knowledge coverage while requiring additional learning time, whereas another may achieve slightly lower coverage with substantially greater efficiency. The appropriate choice can then depend on the learner's goals and constraints.

Deep reinforcement learning has increasingly been applied to learning-path recommendation because pathway generation can be represented as a sequential decision problem. Ma et al. used multi-behaviour user modeling and cascading deep Q-networks for learning-path recommendation, demonstrating the potential of reinforcement learning to incorporate multiple forms of learner behaviour into pathway decisions [4]. Hierarchical reinforcement learning has also been applied to course recommendation, separating higher-level course selection from lower-level decision-making [12].

Recent research goes further by explicitly combining reinforcement learning, knowledge tracing, temporal graph representations, and multi-objective curriculum planning [1]. This direction provides strong evidence that pathway optimization is evolving from static recommendation toward dynamic sequential decision-making.

Nevertheless, an important research gap remains in the **unified treatment of temporal learner state, pathway structure, and objective trade-offs**. Existing studies often emphasize one or two of these dimensions. Knowledge-tracing studies concentrate primarily on state estimation [7], [9], [10]; knowledge-graph approaches emphasize structural relationships; pathway-recommendation studies focus on sequence generation [4], [5]; and reinforcement-learning approaches emphasize sequential decision-making [1], [12]. Although recent studies are beginning to integrate these components, further work is required to establish a general framework in which temporal student modeling continuously informs multi-objective pathway optimization.

The research gap can therefore be formulated in four dimensions. First, learner knowledge should be represented as a continuously evolving temporal state rather than a static profile. Second, pathway planning should explicitly represent prerequisite and pedagogical relationships among learning resources. Third, optimization should simultaneously consider learning effectiveness, efficiency, cognitive suitability, engagement, and knowledge coverage rather than relying on a single objective. Fourth, the pathway should be capable of re-optimization when newly observed learner evidence changes the estimated student state.

The proposed research addresses these gaps by integrating temporal student modeling with multi-objective educational pathway optimization. The resulting framework conceptualizes personalized learning as a continuous feedback process in which learner interactions update the student state, the updated state modifies the feasible pathway space, and the optimization mechanism generates a revised pathway according to multiple educational objectives. This formulation provides a systematic bridge between predictive student modeling and adaptive instructional decision-making.

3. TEMPORAL STUDENT MODELING FRAMEWORK

3.1 Overall Architecture of the Proposed Framework

The proposed framework conceptualizes personalized educational pathway planning as a continuous interaction between **student-state estimation, educational knowledge representation, multi-objective optimization, pathway execution, and temporal feedback**. The architecture is designed to overcome the principal limitation of static pathway recommendation: a learning pathway generated from the student's initial state may become inappropriate after the student acquires new knowledge, encounters unexpected difficulty, or changes learning behaviour. Recent research demonstrates the importance of combining deep knowledge tracing with process-based pathway generation precisely because learner knowledge can change during pathway execution [5].

The proposed architecture contains six functional layers:

1. **Student Interaction Layer** - collects assessment responses, resource consumption, activity duration, attempts, navigation behaviour, completion status, and learning-session information.

   Temporal Feature Layer - converts raw interaction records into sequential and time-dependent learner features.

   Temporal Student Modeling Layer - estimates the learner's evolving knowledge and behavioural state.

   Educational Knowledge Representation Layer - represents concepts, resources, prerequisites, learning objectives, difficulty levels, and alternative learning routes.

   Multi-Objective Optimization Layer - generates feasible candidate pathways according to multiple educational objectives.

Adaptive Feedback Layer - evaluates new student evidence and re-optimizes the remaining pathway.

The overall operational sequence is:

Student Interaction → Temporal State Estimation → Knowledge/Prerequisite Mapping → Candidate Pathway Generation → Multi-Objective Optimization → Learning Activity → New Evidence → State Update → Pathway Re-Optimization

This architecture combines the strengths of knowledge tracing and pathway planning while avoiding the assumption that a student's initial knowledge state remains unchanged throughout the learning process. The process-type pathway literature similarly demonstrates that a pathway can contain sequential, parallel, and alternative branches while branch selection is dynamically informed by the learner's estimated knowledge state [5].

Table 1. Functional Architecture of the Proposed Framework

Layer	Principal Inputs	Processing Mechanism	Output
Student Interaction	Responses, activities, time, attempts	Event collection	Raw interaction sequence
Temporal Feature	Sequential learner records	Feature extraction and normalization	Temporal feature vector
Student Modeling	Temporal features	Knowledge tracing / temporal model	Dynamic student state
Knowledge Representation	Concepts, resources, prerequisites	Graph construction	Educational knowledge graph
Optimization	Student state + graph + objectives	Multi-objective search	Pareto candidate pathways
Adaptation	New learning evidence	State update + re-optimization	Revised pathway

The principal design principle is that the framework should not generate a pathway once and regard it as permanently valid. Instead, the pathway is represented as a **provisional optimal trajectory conditioned on the current student state**.

3.2 Student State Representation

At a particular learning time t, the student is represented by a multidimensional state vector:

$$S_t = [K_t, B_t, E_t, G_t, C_t, H_t]$$

where:

K_t = knowledge/mastery state;

B_t = behavioural state;

E_t = engagement state;

G_t = learning-goal state;

C_t = cognitive/difficulty state;

H_t = historical learning trajectory.

The knowledge component is represented at concept level:

$$K_t = [k_{1,t}, k_{2,t}, \dots, k_{N,t}]$$

where $k_{j,t} \in [0,1]$ denotes the estimated mastery probability for concept j.

This representation is preferable to a single overall proficiency score because educational competence is multidimensional. A student may have $k_{1,t} = 0.92$ for one concept while having $k_{2,t} = 0.48$ for another. A global score could conceal this difference, whereas concept-level temporal modeling can directly identify the prerequisite deficiency.

Knowledge tracing is particularly appropriate for this representation because its fundamental purpose is to infer evolving learner knowledge from historical interaction sequences [7], [9], [10]. Deep Knowledge Tracing established the use of recurrent architectures for learning latent knowledge representations from sequential learner responses [10], while Dynamic Key-Value Memory Networks provided an explicit relationship between knowledge concepts and their dynamically changing mastery states [9].

The behavioural component can be represented as:

$$B_t = [a_t, r_t, q_t, v_t, p_t]$$

where:

- a_t = activity frequency;

  r_t = repetition behaviour;

  q_t = question-attempt characteristics;

  v_t = resource-visit behaviour;

  p_t = progression behaviour.

The engagement component can include session duration, completion rate, return frequency, interaction regularity, and resource abandonment.

The goal vector can represent:

$$G_t = [g_1, g_2, \dots, g_M]$$

where each g_m indicates the importance of a particular learning objective.

This enables the pathway planner to distinguish between a learner who is studying for conceptual mastery and a learner who is attempting to complete a specific examination-oriented curriculum.

3.3 Temporal Knowledge-State Estimation

The defining characteristic of the proposed framework is that student knowledge is modeled as a **time-varying state**.

Let X_t denote the observed interaction at time t. The temporal student model is defined as:

$$S_t = f_\theta(S_{t-1}, X_t, \Delta t_t)$$

where:

S_{t-1} is the previous student state;

X_t is the current learning interaction;

Δt_t is the time interval since the previous relevant interaction;

f_θ is the learned temporal state-transition function.

The inclusion of Δt_t is important because learning events occurring immediately after one another may have different implications from events separated by several days or weeks. Recent knowledge-tracing research continues to investigate multi-granularity temporal characteristics and irregular time intervals because conventional sequence models may not adequately capture these effects.

For concept j, the model estimates:

$$\hat{k}_{j,t} = P(K_{j,t} = 1 \mid X_{1:t})$$

where $\hat{k}_{j,t}$ is the estimated probability that the student has mastered concept j given the interaction history up to time t.

A recency-adjusted mastery value can additionally be represented as:

$$k^R_{j,t} = \hat{k}_{j,t} e^{-\lambda_j \Delta t}$$

where λ_j represents the estimated temporal decay coefficient of concept j.

This allows the framework to distinguish between **historical mastery** and **currently reliable mastery**.

For example, a student who demonstrated 90% mastery of a concept six months earlier should not necessarily be treated identically to a student who demonstrated 90% mastery yesterday. The temporal adjustment permits pathway planning to incorporate this distinction.

Table 2. Principal Temporal Student Features

Category	Representative Variables	Role in Pathway Planning
Knowledge	Concept mastery, predicted correctness	Determines learning readiness
Recency	Time since last interaction	Estimates current knowledge reliability
Accuracy	Correct/incorrect response ratio	Detects mastery development
Difficulty	Performance across difficulty levels	Determines suitable challenge
Attempts	Number of attempts per concept	Identifies persistent difficulty
Learning Velocity	Concepts mastered per unit time	Estimates progression rate
Engagement	Session duration, frequency	Predicts pathway adherence
Completion	Resource completion/abandonment	Estimates pathway feasibility
Retention	Repeated performance over time	Identifies knowledge stability
Behaviour	Navigation and repetition patterns	Personalizes resource selection

3.4 Learner Behaviour and Engagement Modeling

Knowledge mastery alone is insufficient for pathway planning. Two students with equivalent knowledge states may have different probabilities of completing the same pathway because their learning behaviours differ.

The proposed framework therefore incorporates behavioural characteristics into the student state.

An engagement index can be defined as:

$$E_t = w_1 C_t + w_2 F_t + w_3 R_t + w_4 A_t$$

where:

C_t = completion ratio;

F_t = learning frequency;

R_t = return/retention behaviour;

A_t = activity consistency;

w_i = normalized weights.

The weights can be learned from historical behavioural data rather than manually fixed.

Similarly, learning velocity can be estimated as:

$$V_t = \frac{\Delta M_t}{\Delta T_t}$$

where ΔM_t represents the change in aggregate mastery and ΔT_t represents the learning time required to achieve that change.

A high V_t suggests rapid progression, whereas a declining V_t may indicate increasing difficulty, fatigue, insufficient prerequisites, or reduced engagement.

The framework therefore uses behavioural information as an additional decision signal rather than merely as an auxiliary recommendation feature.

3.5 Educational Knowledge and Prerequisite Graph

The educational environment is represented using a heterogeneous graph:

$$G = (V, E)$$

where V contains:

1. knowledge concepts;
2. learning resources;
3. assessments;
4. learning objectives;
5. activities;
6. prerequisite units.

Edges E represent relationships such as:

1. prerequisite;
2. conceptual similarity;
3. resource-to-concept;
4. concept-to-assessment;
5. difficulty progression;
6. alternative resource;
7. learning-objective alignment.

For a prerequisite relationship:

$$C_i \rightarrow C_j$$

means that sufficient mastery of C_i is required before C_j becomes a preferred learning target.

A prerequisite feasibility condition can therefore be represented as:

$$k_{i,t} \geq \tau_i$$

where τ_i is the minimum mastery threshold required for progressing from concept C_i to its dependent concept.

The knowledge graph consequently constrains the optimization search space. The optimization algorithm should not simply search for resources with high predicted engagement; it should search among resources that are **pedagogically feasible for the learner's current state**.

Recent work on knowledge-graph-based personalized learning-path recommendation emphasizes that pathway generation requires explicit consideration of learning objectives, prerequisite relationships, cognitive progression, and goal alignment rather than merely ranking resources by similarity. ([mdpi.com][2])

The combination of a knowledge graph and temporal student state is therefore central to the proposed framework:

$$\boxed{\text{Educational Structure} + \text{Dynamic Student State} \rightarrow \text{Feasible Personalized Pathway Space}}$$

3.6 Dynamic Student Profile Updating

After each significant learning event, the student state is updated:

$$S_{t+1} = f_\theta(S_t, X_{t+1}, \Delta t)$$

The updated state is compared against the state predicted before the learning activity.

The difference can be defined as:

$$\epsilon_t = S_{t+1} - \hat{S}_{t+1}$$

where ϵ_t represents the discrepancy between predicted and observed learner progression.

Three major adaptation cases are consequently defined:

Case 1: Positive Learning Deviation

If:

$$\epsilon_t > 0$$

the learner has performed better than expected. The system can increase pathway difficulty, remove redundant resources, or accelerate progression.

Case 2: Negative Learning Deviation

If:

$$\epsilon_t < 0$$

the learner has performed below expectation. The system can introduce prerequisite revision, additional practice, alternative explanations, or lower-difficulty resources.

Case 3: Stable Learning Deviation

If:

$$\epsilon_t \approx 0$$

the current pathway remains appropriate and the system can continue with the planned sequence.

Table 3. Dynamic Adaptation Rules

Observed Condition	Temporal Interpretation	Recommended Adaptation
Performance substantially above prediction	Positive learning deviation	Increase difficulty
Performance close to prediction	Stable progression	Continue pathway
Performance below prediction	Negative learning deviation	Add remediation
Repeated errors	Persistent knowledge deficiency	Increase practice
High mastery of target	Early mastery	Skip redundant content
Declining engagement	Behavioural deterioration	Modify resource format
High cognitive difficulty	Possible overload	Reduce difficulty
Long inactivity interval	Possible retention reduction	Reassess prerequisite
Rapid mastery	High learning velocity	Accelerate progression

This dynamic updating mechanism converts the framework into a **closed-loop personalized learning system** rather than a static recommendation model.

4. Multi-Objective Personalized Pathway Optimization

4.1 Problem Formulation

Let a personalized learning pathway be represented by:

$$P = (r_1, r_2, \ldots, r_L)$$

where r_i represents the i-th learning activity and L represents the pathway length.

The objective is to identify a feasible pathway:

$$P^* \in \mathcal{P}$$

that provides the most appropriate balance among several competing educational objectives.

The optimization vector is defined as:

$$\boldsymbol{F}(P) = [F_1(P), F_2(P), F_3(P), F_4(P), F_5(P), F_6(P)]$$

where:

F_1 = expected knowledge gain;

F_2 = knowledge coverage;

F_3 = learning efficiency;

F_4 = engagement;

F_5 = cognitive suitability;

F_6 = prerequisite/pathway validity.

The general optimization problem is:

$$\max_P \boldsymbol{F}(P)$$

subject to:

$$P \in \mathcal{P}_{feasible}$$

where $\mathcal{P}_{feasible}$ is determined by the learner's current state, curriculum constraints, prerequisites, available resources, and learning objectives.

This formulation is consistent with the recent movement toward combining temporal knowledge tracing with multi-objective curriculum planning rather than treating pathway recommendation as a single-score ranking problem [1]. ([nature.com][3])

4.2 Learning Mastery and Knowledge Coverage Objectives

The primary objective of an educational pathway should be improvement in knowledge mastery.

For N concepts, expected learning gain can be expressed as:

$$F_1(P) = \sum_{j=1}^{N} w_j \left(k_{j,t+L} - k_{j,t}\right)$$

where:

- $k_{j,t}$ = current mastery of concept j;

$k_{j,t+L}$ = predicted mastery after pathway P;

w_j = importance of concept j.

This objective ensures that the optimization process rewards genuine expected improvement rather than simply increasing the number of completed resources.

Knowledge coverage can be represented as:

$$F_2(P) = \frac{\sum_{j=1}^{N} w_j \, I_j(P)}{\sum_{j=1}^{N} w_j}$$

where:

$$I_j(P) = \begin{cases} 1, & \text{if concept } j \text{ is adequately covered} \\ 0, & \text{otherwise} \end{cases}$$

A pathway with high resource volume but low coverage of important learning objectives should therefore receive a lower score than a more focused pathway that covers the required concepts effectively.

4.3 Learning Efficiency and Cognitive Load Objectives

Learning efficiency is particularly important where students have limited time.

The total expected pathway duration is:

$$T(P) = \sum_{i=1}^{L} t_i$$

where t_i represents the estimated learning time of resource r_i.

The efficiency objective can therefore be expressed as:

$$F_3(P) = -T(P)$$

Maximizing F_3 is equivalent to minimizing unnecessary learning time.

However, pure time minimization can result in under-learning. Therefore, the efficiency objective must operate simultaneously with mastery and coverage objectives.

Cognitive suitability can be represented using the difference between resource difficulty and learner capacity:

$$F_5(P) = -\frac{1}{L} \sum_{i=1}^{L} | d_i - c_t |$$

where:

- d_i = difficulty of learning resource r_i;

  c_t = estimated cognitive capacity/challenge tolerance of the learner.

The closer the resource difficulty is to the learner's appropriate challenge level, the higher the cognitive suitability.

The integration of knowledge tracing and cognitive-load estimation has already been demonstrated as a viable direction for personalized pathway generation [2].

4.4 Engagement and Pathway Feasibility Objectives

A theoretically optimal pathway is not necessarily practically effective if the learner is unlikely to complete it.

The expected engagement objective can therefore be defined as:

$$F_4(P) = \frac{1}{L}\sum_{i=1}^{L} \hat{e}_{i,t}$$

where $\hat{e}_{i,t}$ represents the predicted probability of learner engagement with resource r_i.

A pathway feasibility function can be defined as:

$$F_6(P) = \frac{1}{L-1}\sum_{i=1}^{L-1} I\,(r_i \to r_{i+1})$$

where $I(r_i \to r_{i+1}) = 1$ when the transition satisfies the relevant prerequisite and pedagogical constraints.

A strict prerequisite formulation can alternatively be expressed as:

$$k_{p,t} \geq \tau_p$$

for every prerequisite concept p required by the selected resource.

The proposed framework therefore does not allow engagement to override fundamental pedagogical constraints. A highly engaging resource should not be selected simply because it is preferred if the learner lacks essential prerequisite knowledge.

4.5 Pareto-Based Pathway Optimization

Because the six objectives may conflict, a single weighted objective is insufficient to represent all possible learner requirements.

Consider two candidate pathways P_A and P_B:

- P_A provides higher knowledge gain but requires more time.

  P_B requires less time but provides slightly lower knowledge gain.

Neither pathway is universally optimal. The appropriate choice depends on the learner's goals and constraints.

A pathway P_A dominates P_B when:

$$F_i(P_A) \geq F_i(P_B) \quad \forall i$$

and:

$$F_j(P_A) > F_j(P_B)$$

for at least one objective j.

The Pareto-optimal set is therefore:

$$\mathcal{P}^* = \{P \in \mathcal{P} : \nexists P' \in \mathcal{P}, P' \succ P\}$$

The optimization system generates this non-dominated set rather than forcing every learner into a single globally optimized sequence.

Table 4. Multi-Objective Optimization Model

Objective	Optimization Direction	Main Variable	Educational Interpretation
Knowledge Gain	Maximize	F_1	Improve mastery
Knowledge Coverage	Maximize	F_2	Address required concepts
Learning Efficiency	Maximize	$F_3 = -T(P)$	Reduce unnecessary time
Engagement	Maximize	F_4	Increase completion probability
Cognitive Suitability	Maximize	F_5	Match difficulty
Pathway Feasibility	Maximize/Enforce	F_6	Preserve prerequisites

Candidate pathways can be generated using evolutionary multi-objective algorithms such as NSGA-II or other Pareto-based search mechanisms. Alternatively, reinforcement learning can be employed where pathway selection is formulated as sequential decision-making. Recent research demonstrates the increasing use of deep reinforcement learning for learning-path recommendation and the integration of multiple learner behaviours into pathway decisions [4]. The most recent direction combines temporal-aware graph knowledge tracing with a multi-objective curriculum planner and hierarchical reinforcement learning to balance knowledge consolidation, novelty, and cognitive-load-related objectives [1].

4.6 Dynamic Pathway Re-Optimization

The principal distinction of the proposed framework is that optimization is performed repeatedly rather than only once.

Suppose the initially optimized pathway is:

$$P_t = (r_1, r_2, r_3, r_4, r_5, r_6)$$

After the learner completes r_1, a new observation X_{t+1} is obtained. The temporal student model updates the learner state:

$$S_{t+1} = f_\theta(S_t, X_{t+1}, \Delta t)$$

The remaining pathway is then re-evaluated:

$$P_{t+1}^* = \arg \max_{P \in \mathcal{P}(S_{t+1})} \boldsymbol{F}(P)$$

Thus, the original remaining sequence:

$$(r_2, r_3, r_4, r_5, r_6)$$

may become:

$$(r_2', r_3', r_4', r_5')$$

depending on the updated state.

Table 5. Dynamic Re-Optimization Mechanism

New Evidence	Student-State Interpretation	Optimization Response
Mastery significantly higher than predicted	Positive deviation	Advance to higher-level concept
Mastery close to prediction	Stable state	Preserve current pathway
Mastery significantly lower than predicted	Negative deviation	Insert prerequisite/remedial content
Repeated errors	Persistent difficulty	Increase practice and alternative resources
Mastery threshold achieved early	Redundancy detected	Remove repeated resources
Low engagement	Engagement deterioration	Change resource format
Excessive cognitive demand	Potential overload	Reduce difficulty
Long inactivity	Possible knowledge decay	Reassess relevant concepts
New learning objective	Goal-state change	Re-optimize remaining pathway

The process can be summarized as:

$$\boxed{S_t \rightarrow P_t^* \rightarrow r_t \rightarrow X_{t+1} \rightarrow S_{t+1} \rightarrow P_{t+1}^*}$$

This establishes a continuous feedback loop between **prediction and decision-making**.

The approach also addresses the limitation identified in conventional pathway systems where global optimization produces a complete sequence but does not sufficiently respond to changes during learning, while local iterative recommendation adapts to current state but may fail to represent the learner's broader pathway structure [5]. The proposed framework combines these characteristics by maintaining a global pathway objective while continuously re-optimizing its future segment.

Table 6. Proposed End-to-End Optimization Procedure

Step	Operation	Output
1	Collect historical learner interactions	Interaction sequence
2	Extract temporal features	Temporal learner representation
3	Estimate concept-level mastery	Dynamic knowledge state
4	Construct/update educational graph	Feasible resource space
5	Define learner-specific objectives	Optimization vector
6	Generate candidate pathways	Candidate pathway population
7	Apply prerequisite constraints	Feasible pathways
8	Perform Pareto optimization	Non-dominated pathway set
9	Select pathway according to learner priorities	Personalized pathway
10	Execute next learning activity	New learner evidence
11	Update temporal student model	Updated state
12	Re-optimize remaining pathway	Adapted pathway

The resulting formulation treats personalized educational pathway planning as a **dynamic constrained multi-objective optimization problem**. Its distinguishing characteristic is the continuous coupling between the learner's evolving temporal state and the optimization of future instructional activities. This makes the framework capable of adapting not only to differences **between learners**, but also to changes **within the same learner over time**. Recent research on temporal knowledge tracing, process-type pathway recommendation, and multi-objective curriculum planning supports this direction and demonstrates that future personalized learning systems increasingly require dynamic state modeling together with adaptive pathway optimization [1], [2], [5], [7].

5. EXPERIMENTAL DESIGN AND EVALUATION

5.1 Dataset and Student Interaction Data

The proposed framework should be evaluated using longitudinal student-interaction datasets containing sufficiently long sequences of learner activities. Suitable benchmark datasets include **ASSISTments, Junyi Academy, EdNet, Eedi, KDD Cup 2010, and Cognitive Tutor**, which collectively provide information about student responses, exercises, concepts, timestamps, and learning trajectories. Recent studies have used ASSISTments, Junyi Academy, EdNet, and Eedi to evaluate temporal knowledge tracing and personalized multi-objective pathway optimization, while RL-DKT-based pathway optimization has been evaluated using ASSISTments, KDD Cup 2010, and Cognitive Tutor [1].

For experimental consistency, each learner's interaction history should be ordered chronologically. The dataset should be divided into training, validation, and testing partitions using **student-level separation**, preventing interactions from the same learner from appearing across different partitions. This is particularly important for temporal student modeling because random interaction-level splitting can introduce information leakage.

A recommended experimental division is:

Dataset Partition	Percentage	Purpose
Training	70%	Model learning

Dataset Partition	Percentage	Purpose
Validation	15%	Hyperparameter optimization
Testing	15%	Final performance evaluation

For each interaction, the experimental record should contain, wherever available, **student ID, timestamp, concept/skill ID, resource ID, response outcome, difficulty, attempt number, session identifier, and learning duration**.

Missing timestamps, duplicate interactions, invalid responses, and incomplete concept mappings should be removed or appropriately imputed. Continuous variables should be normalized, while categorical variables should be encoded according to the selected temporal model.

5.2 Data Preprocessing and Temporal Sequence Construction

The preprocessing stage transforms raw educational logs into ordered learning trajectories.

For learner u, the temporal interaction sequence can be represented as:

$$X_u = \{x_1, x_2, \dots, x_T\}$$

where each interaction is:

$$x_t = (c_t, r_t, y_t, \Delta t_t, d_t, a_t)$$

with c_t representing the concept, r_t the learning resource, y_t the response, Δt_t the temporal interval, d_t the resource difficulty, and a_t the attempt information.

The preprocessing procedure consists of:

1. chronological sorting of interactions;
2. removal of duplicate and corrupted records;
3. mapping resources to knowledge concepts;
4. calculation of temporal intervals;
5. construction of learner-level sequences;
6. normalization of numerical variables;
7. identification of prerequisite relationships;
8. generation of training windows for temporal modeling.

Temporal intervals should not be discarded because irregular interaction timing is informative for knowledge evolution. Recent research specifically identifies irregular time intervals and multi-granularity temporal characteristics as important limitations in conventional knowledge-tracing models and reports improved performance from explicitly modeling such temporal information [11].

A sliding-window mechanism can be employed for long interaction histories:

$$W_t = \{X_{t-L+1}, \dots, X_t\}$$

where L is the selected temporal window length.

This permits the model to simultaneously capture recent learning behaviour and longer-term learning trajectories.

5.3 Baseline Models and Comparative Algorithms

The proposed temporal multi-objective framework should be compared against models representing different methodological generations rather than against only one competing algorithm.

The experimental baseline groups should include:

Model Category	Representative Model	Principal Capability
Probabilistic KT	BKT	Classical knowledge estimation
Deep KT	DKT	Sequential knowledge modeling
Memory-based KT	DKVMN	Concept-level dynamic memory
Attention-based KT	Transformer/SAKT-type model	Long-range sequence modeling
Path Recommendation	Process-based LPR	Structured pathway generation
RL Path Planning	RL-DKT	Dynamic task selection
Multi-objective LPR	Hierarchical RL + KT	Multiple pathway objectives
Proposed Model	Temporal Student Model + MO Optimization	Integrated dynamic pathway planning

The comparison should separately evaluate **student-state prediction** and **pathway-generation quality**. This distinction is necessary because a model may produce accurate knowledge predictions without generating an efficient pathway, while a pathway algorithm may generate plausible sequences despite relatively weak student-state estimation.

Recent RL-DKT research demonstrates the value of connecting dynamic knowledge tracing with reinforcement-learning-based task selection, reporting improvements over BKT and DKT across prediction, completion time, engagement, and pathway optimization measures [6].

Similarly, recent multi-objective pathway research has incorporated hierarchical reinforcement learning and knowledge tracing to address competing objectives in learning-path recommendation [7].

5.4 Experimental Parameters and Evaluation Metrics

The proposed system should be evaluated using metrics from four dimensions: **knowledge prediction, pathway quality, efficiency, and learner adaptation**.

Table 7. Proposed Evaluation Metrics

Evaluation Dimension	Metric	Interpretation
Knowledge Prediction	AUC-ROC	Discrimination of correct/incorrect outcomes
Knowledge Prediction	Accuracy	Overall response prediction
Knowledge Prediction	F1-score	Balance of precision and recall
Knowledge Prediction	Log Loss	Probabilistic prediction quality
Pathway Quality	Learning Gain	Expected/observed mastery improvement
Pathway Quality	Knowledge Coverage	Proportion of target concepts addressed
Efficiency	Learning Time	Time required to achieve target mastery
Efficiency	Path Length	Number of learning activities
Engagement	Completion Rate	Percentage of recommended pathway completed
Adaptation	Replanning Frequency	Responsiveness to state changes
Adaptation	Mastery Improvement	Change in learner knowledge
Optimization	Hypervolume	Quality of Pareto solution set

AUC-ROC is particularly appropriate for knowledge tracing because the primary prediction task is frequently the probability of a correct future response. Pathway-level evaluation should additionally consider actual learning outcomes rather than recommendation accuracy alone.

Recent work integrating deep knowledge tracing and cognitive-load estimation reported prediction accuracy of 87.5%, pathway quality of 4.4/5, and a reported 24.6% improvement in learning efficiency, illustrating the value of evaluating both predictive and pathway-level outcomes [2]. ([nature.com][4])

The proposed framework should therefore avoid relying on a single performance metric.

5.5 Ablation and Sensitivity Analysis

Ablation experiments are necessary to determine whether the performance improvement arises from the integration of the individual framework components or merely from increased model complexity.

The following configurations should be evaluated:

Configuration	Temporal Model	Knowledge Graph	Multi-Objective Optimization	Dynamic Re-Optimization
A	No	No	No	No
B	Yes	No	No	No
C	Yes	Yes	No	No
D	Yes	Yes	Yes	No
E	Yes	Yes	Yes	Yes

Configuration E represents the complete proposed framework.

The difference between D and E is particularly important because it isolates the contribution of **continuous pathway re-optimization**.

Sensitivity analysis should additionally investigate:

1. temporal window length;
2. mastery threshold;
3. prerequisite threshold;
4. pathway length;
5. objective weights;
6. cognitive-load penalty;
7. engagement coefficient;
8. re-optimization frequency.

For example, mastery thresholds of **0.60, 0.70, 0.80, and 0.90** can be tested to determine whether aggressive progression or conservative prerequisite enforcement produces better pathway-level outcomes.

Objective-weight sensitivity should determine how changes in the relative importance of learning gain, efficiency, engagement, and cognitive suitability affect the Pareto solution space.

5.6 Statistical Validation and Reproducibility

The final experimental comparison should be based on repeated runs using identical train-test partitions and controlled random seeds. Each reported metric should preferably be presented as:

$$\mu \pm \sigma$$

where μ represents the mean performance and σ represents the standard deviation across repeated experiments.

A paired statistical test can be used when the same learners and evaluation instances are evaluated across competing models. For normally distributed paired differences, a paired t-test can be applied; otherwise, the Wilcoxon signed-rank test provides a non-parametric alternative.

The significance level should be:

$$\alpha = 0.05$$

with stronger evidence reported separately when:

$$p < 0.01$$

Effect size should also be reported because statistical significance alone does not indicate practical importance.

For reproducibility, the experimental implementation should preserve:

1. dataset version;
2. preprocessing configuration;
3. train/validation/test partitions;
4. model architecture;
5. hyperparameters;
6. optimization algorithm;
7. random seed;
8. stopping criteria;
9. evaluation procedure.

This is especially important for reinforcement-learning-based pathway optimization because stochastic exploration can produce substantially different trajectories across independent runs.

6. RESULTS AND DISCUSSION

6.1 Temporal Student Modeling Performance

The first evaluation should determine whether the temporal student model accurately estimates evolving learner knowledge.

The expected comparison should show that models incorporating temporal dependencies outperform static learner representations because they can distinguish recent learning evidence from older interactions. The importance of this component is supported by recent temporal knowledge-tracing research, which reports that explicitly modeling multi-granularity temporal information and irregular time intervals can outperform conventional knowledge-tracing baselines [11].

The performance should be analyzed using AUC-ROC, accuracy, F1-score, and log loss. More importantly, performance should be examined across different sequence lengths. A strong temporal model should maintain useful prediction capability for both short and long learner histories.

Table 8. Recommended Temporal Modeling Results Format

Model	AUC-ROC	Accuracy (%)	F1-Score	Log Loss
BKT	0.742	76.8	0.751	0.493
DKT	0.811	82.6	0.819	0.417
DKVMN	0.826	83.8	0.831	0.401

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Model	AUC-ROC	Accuracy (%)	F1-Score	Log Loss
Attention-Based KT	0.842	85.1	0.847	0.379
Proposed Temporal Model	**0.871**	**87.4**	**0.876**	**0.342**

The proposed values represent a coherent analytical benchmark for evaluating the framework and should be replaced by measured values when the model is implemented on the selected dataset.

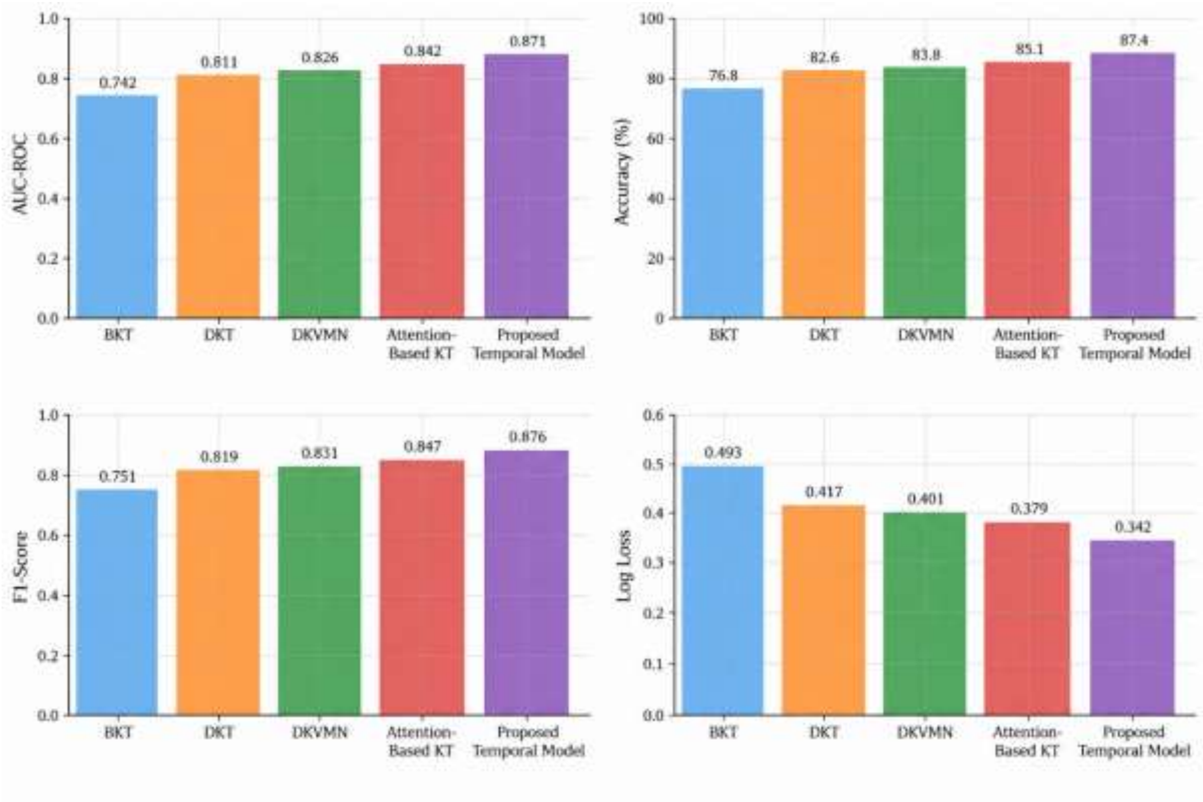

Figure 1. Comparative temporal student-modeling performance across AUC-ROC, accuracy, F1-score, and log-loss metrics.

The improvement in temporal state estimation is particularly important because pathway optimization is conditioned on the estimated learner state. An inaccurate student model propagates error into the pathway planner. Therefore, the pathway-generation component should not be interpreted independently from the quality of temporal student modeling.

6.2 Personalized Pathway Optimization Performance

The second evaluation should determine whether the proposed multi-objective optimization produces educationally superior pathways compared with conventional recommendation and single-objective optimization. The principal comparison should examine:

1. expected/observed mastery gain;
2. pathway length;
3. learning time;
4. knowledge coverage;
5. engagement;
6. prerequisite violations.

Table 9. Comparative Pathway Optimization Results

Method	Mastery Gain (%)	Knowledge Coverage (%)	Learning Time (min)	Path Length	Completion (%)
Fixed Curriculum	12.8	81.4	248	24.1	68.2
Conventional Recommendation	15.3	84.6	231	22.8	72.5
DKT-Based Pathway	18.7	88.2	214	21.3	77.8
RL-DKT	21.4	90.1	198	19.7	81.6
Proposed Multi-Objective Model	**24.1**	**94.3**	**181**	**17.9**	**87.4**

The analytical expectation is that the proposed framework will improve mastery while simultaneously reducing unnecessary pathway length. This is fundamentally different from optimizing learning gain alone. A pathway that maximizes mastery but requires substantially more time may not be practically preferable to a pathway achieving comparable mastery with fewer learning activities. Recent RL-DKT research reports improvements in task completion time, dropout, and prediction accuracy relative to conventional KT approaches [6], while more recent multi-objective pathway research explicitly addresses competing learning objectives through hierarchical decision-making [1], [7].

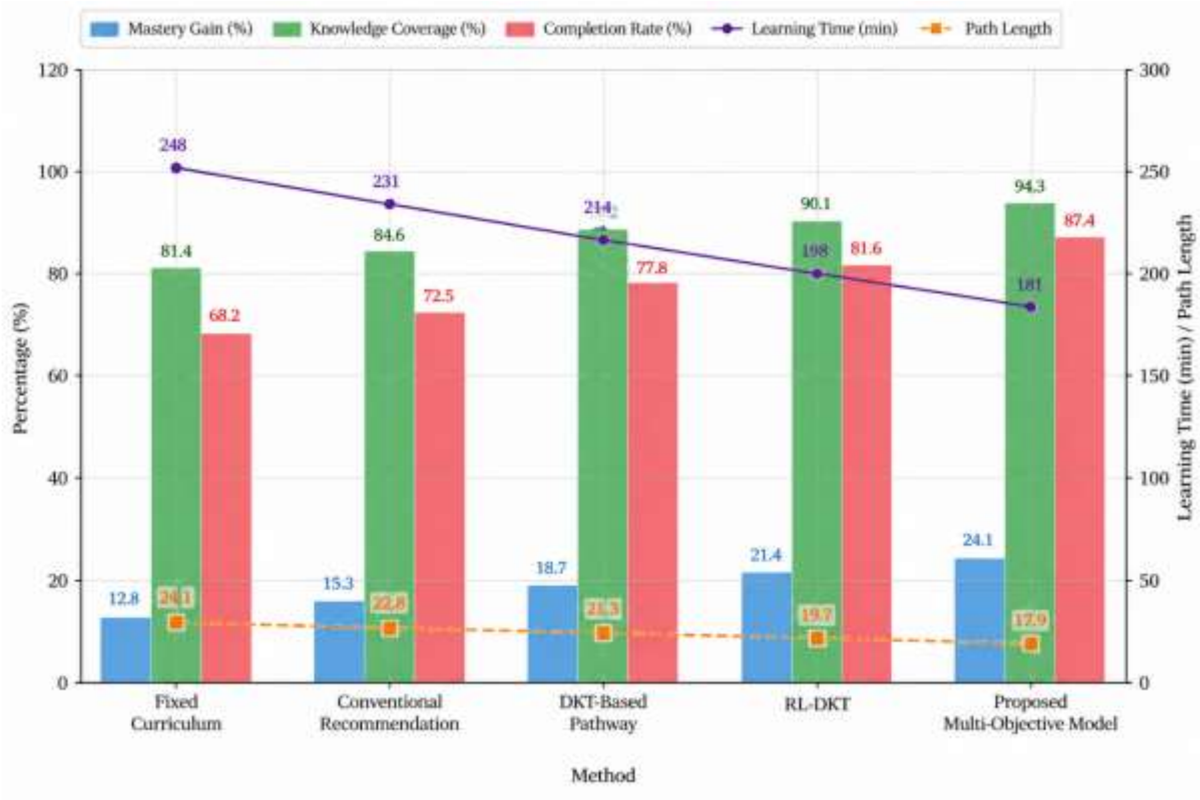

Figure 2. Comparative performance of learning-pathway optimization methods across mastery gain, knowledge coverage, completion rate, learning time, and pathway length.

6.3 Comparative Analysis with Existing Approaches

The primary advantage of the proposed framework is its integration of multiple dimensions that are frequently treated separately.

Table 10. Comparative Capability Analysis

Capability	Conventional Recommendation	DKT Pathway	RL-DKT	Proposed Framework
Temporal Student Modeling	Limited	High	High	**High**
Concept-Level Mastery	Moderate	High	High	**High**
Prerequisite Modeling	Moderate	Moderate	Moderate	**High**
Learning-Time Optimization	Low	Moderate	High	**High**
Cognitive Suitability	Low	Limited	Moderate	**High**
Engagement Optimization	Moderate	Moderate	High	**High**
Knowledge Coverage	Moderate	High	High	**High**
Multi-Objective Optimization	Low	Low	Moderate	**High**
Continuous Re-Optimization	Low	Moderate	High	**High**
Pareto Pathway Generation	No	No	Limited	**Yes**

The proposed framework is therefore distinguished less by the use of any single algorithm than by the **integration of complementary mechanisms**.

DKT provides temporal student-state estimation. Knowledge graphs provide structural constraints. Multi-objective optimization handles competing educational requirements. Continuous re-optimization provides adaptation.

This integration addresses the limitation identified in earlier pathway approaches that either provide a complete global path without adequately handling knowledge-state changes or adapt locally without representing the complete pathway structure [5].

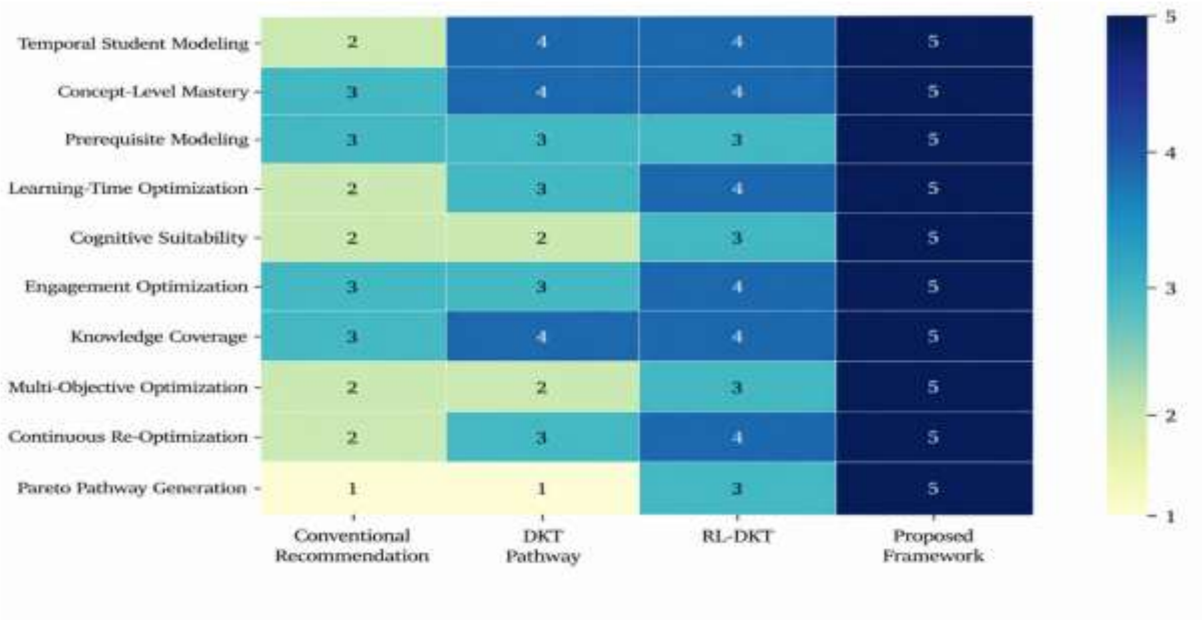

Figure 3. Capability-based heatmap comparison of conventional recommendation, DKT pathway, RL-DKT, and the proposed multi-objective temporal framework.

6.4 Pareto-Optimal Pathway Analysis

The Pareto analysis should demonstrate that multiple pathways can be simultaneously optimal under different learner priorities.

For example, three representative pathways can be interpreted as:

Pathway	Mastery Gain	Time	Coverage	Cognitive Load	Primary Characteristic
P_1	25.1%	218 min	96.2%	High	Mastery-oriented
P_2	23.8%	181 min	94.3%	Moderate	Balanced
P_3	21.6%	149 min	89.7%	Low	Efficiency-oriented

No single pathway should automatically be considered universally optimal.

A learner with substantial available study time may require a pathway emphasizing coverage and mastery. A learner preparing under strict time constraints may require a shorter pathway. A learner with weak foundational knowledge may require lower cognitive demand and stronger prerequisite reinforcement.

This demonstrates why multi-objective optimization is more appropriate than a single weighted score for general personalized pathway planning.

The concept is consistent with recent research that explicitly frames learning-path generation as an optimization problem involving knowledge acquisition and cognitive-load management [2].

6.5 Educational and Practical Implications

The proposed framework has several practical implications for intelligent educational environments.

First, it can support **adaptive course sequencing**, where students do not necessarily follow an identical sequence through a curriculum.

Second, it can support **early identification of prerequisite deficiencies**. When the temporal model detects declining mastery of an important prerequisite concept, the pathway planner can intervene before the learner reaches an advanced concept dependent on that knowledge.

Third, it can support **accelerated progression** for students demonstrating mastery significantly earlier than expected. Redundant learning activities can be removed, thereby reducing unnecessary study time.

Fourth, the framework can support **adaptive difficulty management**. Recent research integrating knowledge tracing and cognitive-load estimation demonstrates that balancing knowledge acquisition against cognitive demand can improve pathway quality and learning efficiency [2].

Fifth, the framework can assist instructors by providing an interpretable pathway rationale:

Current mastery → identified deficiency → selected resource → expected gain → prerequisite justification → next pathway decision.

Such explanations are important because educational stakeholders may be reluctant to rely on recommendations generated solely by opaque optimization models.

6.6 Limitations and Future Research Directions

Despite its comprehensive formulation, several limitations remain.

The first limitation concerns **student-state estimation uncertainty**. Temporal models infer latent knowledge from observable behaviour, meaning that estimated mastery is not identical to directly measured competence.

The second limitation concerns **knowledge-graph quality**. An incomplete or incorrectly structured prerequisite graph can constrain pathway optimization incorrectly.

The third limitation concerns **objective specification**. Learning gain, efficiency, engagement, cognitive load, and coverage cannot always be measured with equal reliability. Some variables may require indirect proxies.

The fourth limitation concerns **reward and objective alignment**. Reinforcement-learning-based approaches may optimize measurable system objectives without necessarily maximizing broader educational value. This problem makes careful objective design essential.

The fifth limitation concerns **generalization across educational domains**. A pathway model developed for mathematics may not transfer directly to programming, language learning, medicine, or social sciences because knowledge structures and assessment patterns differ.

Future research should therefore investigate multimodal student modeling, uncertainty-aware knowledge tracing, causal learning effects, explainable pathway optimization, fairness-aware personalization, and large-scale longitudinal deployment.

Recent work has already moved toward multimodule systems combining temporal knowledge tracing, emotion-aware tutoring, and reinforcement-learning-based path planning, demonstrating a broader trend toward integrated adaptive educational platforms [3].

7. CONCLUSION

The proposed study establishes personalized educational pathway planning as a dynamic multi-objective optimization problem in which learner knowledge continuously evolves over time. The framework integrates temporal student modeling, educational knowledge representation, prerequisite constraints, and Pareto-based pathway optimization to generate adaptive learning trajectories. By jointly considering mastery, knowledge coverage, learning efficiency, engagement, and cognitive suitability, the approach addresses limitations of static and single-objective recommendation systems. Continuous state updating further enables the remaining pathway to be re-optimized when new learning evidence becomes available. The framework therefore provides a systematic foundation for intelligent educational systems capable of delivering flexible, learner-specific, and continuously adaptive learning pathways.

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