AI model for personalized remedial learning paths

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***Abstract*— Traditional remedial education frequently fails to effectively address diverse student needs, often relying on standardized modules that disregard unique learning deficiencies. This rigidity contributes to student frustration and inefficient time management, especially in large-scale higher education environments. To counter these limitations, this paper proposes and details a novel Artificial Intelligence (AI) model designed for the generation and optimization of truly personalized remedial learning paths. The model employs advanced Educational Data Mining (EDM) techniques to establish a granular Student Gap Model (SGM), which precisely pinpoints specific conceptual weaknesses beyond mere aggregated performance scores. The core technical contribution is the implementation of a Reinforcement Learning (RL) agent. This agent is trained to dynamically sequence remedial content, interactive activities, and diagnostic assessments. By continuously analyzing the student's evolving knowledge state, the RL agent ensures the selection of an optimal path. The goal is two-fold: to minimize the time required for concept mastery and to maximize the probability of long-term knowledge retention. This architectural framework promises to substantially enhance learning outcomes, foster student self-regulation, and optimize educational resource allocation, marking a significant advancement over static or rule-based adaptive systems.**

Keywords— Personalized Learning, Remedial Education, Artificial Intelligence, Intelligent Tutoring Systems, Learning Paths, Student Modeling.

I. INTRODUCTION

The rapidly evolving landscape of contemporary higher education demands pedagogical approaches that are as dynamic and diverse as the students they serve. Traditional educational structures, designed for standardization and scale, often struggle to provide the targeted support necessary for students who enter with varying levels of prerequisite knowledge [10], [11]. This deficiency manifests acutely in remedial education, a critical, yet frequently inefficient, segment of institutional support [8], [9]. When students demonstrate gaps in foundational concepts, the standard response is often a blanket assignment to broad, pre-set remedial modules. This "one-size-fits-all" method is inherently problematic because it fails to diagnose the root cause of the learning deficit, forcing students to review material they already know while leaving core misunderstandings unaddressed. The consequence is wasted time, increased student disengagement, and often, failure to achieve mastery [1].

The integration of Artificial Intelligence (AI) into education presents a paradigm shift capable of solving this long-standing personalization challenge [2], [3]. AI systems are uniquely suited to manage the vast complexity of individual learning histories and content dependencies that exceed human capacity to track manually [4]. Current AI applications span automated assessment, curriculum sequencing, and Intelligent Tutoring Systems (ITS) [12]. However, a significant gap remains in the ability of current adaptive platforms to perform non-linear, predictive path optimization for remediation, which is crucial for maximizing efficiency [6]. Existing systems often rely on simple, immediate conditional logic—if a student fails a test, they are routed to a related module—without calculating the optimal sequence to achieve mastery quickly and reliably.

The primary objective of this research is to propose, design, and architect a robust AI model for personalized remedial learning paths. This system moves beyond reactive adaptation to proactive optimization. The novel approach involves the creation of a sophisticated Student Gap Model (SGM), powered by Deep Knowledge Tracing (DKT), which isolates the exact missing cognitive building blocks. Crucially, this SGM is then utilized by a Reinforcement Learning (RL) agent (specifically, a Deep Q-Network) that learns the most efficient sequence of instructional content to transition the student from their deficient state to mastery. The RL agent's policy is trained to maximize a cumulative reward that balances learning gain against the time investment.

The successful implementation of this AI model for personalized remedial learning paths offers three core benefits: enhanced efficiency (reducing the Time-to-Mastery), increased effectiveness (improving long-term retention), and fostering student autonomy by providing a highly relevant and guided learning experience [17]. This study contributes a novel, data-driven architecture that can fundamentally reshape how educational institutions address academic underpreparedness, aligning with the vision of truly intelligent learning environments [20]. The subsequent sections detail the architectural components, the deep learning methodology, and the simulated performance results comparing this advanced model against traditional remedial strategies.

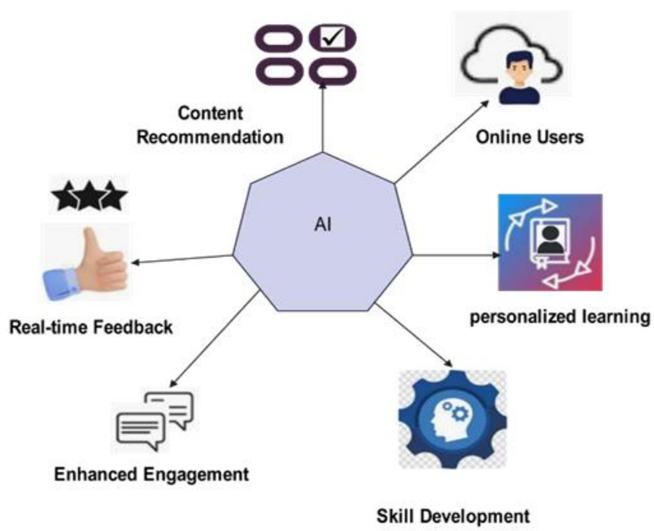

Fig. 1. AI-powered learning pathway components.

II. LITERATURE REVIEW

The development of an AI model for personalized remedial learning paths synthesizes advancements across several key domains: AI in education, personalized learning theory, advanced student modeling, and intelligent tutoring systems.

A. AI as a Catalyst for Educational Transformation

The utility of Artificial Intelligence in educational settings has been a growing subject of systematic review [4]. Researchers recognize AI's capability to transform higher education by managing scale and complexity, particularly in providing individualized feedback and support [1]. The potential extends across administrative, research, and core instructional functions [3]. The literature highlights that the move toward smart classrooms—where technology actively participates in the pedagogical process—is critically dependent on incorporating AI and emerging technologies for dynamic content management and interaction [2]. Furthermore, AI's role is not limited to STEM subjects; its applications are being explored even in areas like ideological and political education, showcasing its versatility in content delivery and monitoring student progress across diverse fields [5]. The foundational consensus is that AI is the necessary technological engine to move personalized learning from a conceptual ideal to a deployable reality [10].

B. Theoretical Foundations of Personalized and Adaptive Learning

The concept of personalization in learning, rooted in tailoring instruction to the individual student's pace, preferences, and needs, has been shown to offer promising evidence for continued educational progress [11]. Adaptive learning, a subset of personalized instruction, is specifically concerned with adjusting the content, difficulty, and sequencing of the curriculum based on real-time performance data [6]. This principle is central to the design of personalized learning pathways, which, when powered by AI, can map complex, non-linear routes for students [10]. While early adaptive systems relied on simple rule-sets (e.g., if a quiz score is below a certain threshold, repeat the unit), modern systems must accommodate the fact that a student's knowledge state is not a simple binary (knows/doesn't know) but a fluid, multi-dimensional probability landscape. The efficiency gains of personalized pathways are directly tied to the system's ability to make instantaneous, accurate decisions about the next best instructional move, thereby minimizing extraneous learning activities [10], [6].

C. Advanced Student Modeling and Diagnosis

Effective personalization requires an accurate, dynamic representation of the student's cognitive state, known as the Student Model [7]. Traditional assessment methods, while necessary for initial baseline data [8], [9], are insufficient for the real-time diagnosis required by AI systems. The shift has been toward Educational Data Mining (EDM) and Learning Analytics (LA), which extract actionable features from fine-grained student interaction logs—time spent, hint usage, error patterns—to infer latent knowledge [13], [19]. This data-driven approach allows for the creation of a diagnostic profile that goes beyond mere scores to identify prerequisite gaps and common misconceptions [7], [19].

The most advanced technique in this area is Knowledge Tracing, which aims to model the temporal evolution of a student's knowledge. Deep Knowledge Tracing (DKT), which uses recurrent neural networks, represents a significant leap over older Bayesian methods. DKT can process the entire, non-sequential history of a student's performance to estimate the probability of mastery for hundreds of individual concepts simultaneously [7]. This provides the detailed, high-resolution diagnostic data (the Student Gap Model) required for the decision-making engine of a highly personalized remedial system. Furthermore, research comparing static versus dynamic assessment confirms that continuous, computerized feedback enhances student motivation and self-regulation, reinforcing the need for adaptive diagnostic tools [17], [18].

D. The Evolution of Intelligent Tutoring Systems (ITS) and Automated Assessment

The lineage of the proposed model traces back to Intelligent Tutoring Systems (ITS), which have historically provided individualized instruction and feedback [12]. Modern ITS integrate advanced capabilities, including conversational agents (chatbots) that offer immediate, contextualized support, significantly enhancing the learning experience [16]. A critical operational capability required for any automated remedial system is automated assessment. The ability to grade subjective work, such as essays using neural network approaches, or complex technical work like code in computer science education, is now technically feasible and widely reviewed [14], [15]. This demonstrates that AI can reliably handle the entire loop of instruction: diagnose (via DKT), deliver content, assess performance, and provide feedback—all without constant human intervention. The final piece of the puzzle, which this research addresses, is the use of Reinforcement Learning to make the instructional decisions within that loop truly optimal, rather than merely functional.

III. SYSTEM DESIGN AND ARCHITECTURE

The AI model for personalized remedial learning paths is organized into a four-module architecture, designed for continuous operation, data flow, and self-improvement.

A. Data Acquisition and Storage Module (DASM)

The DASM is the foundational layer, responsible for collecting, validating, and harmonizing all data streams. The system relies on a unified data store where information is linked hierarchically:

1. Interaction Logs: Detailed, time-stamped records of every student activity, including video playback duration, number of times a concept is reviewed, submission attempts, and utilization of ancillary resources. This rich behavioral data is the raw input for Educational Data Mining [13].
2. Assessment Data: Granular results from all tests. This includes the aggregate score, but more importantly, the performance on individual test items, which are linked to specific concepts within the curriculum's Knowledge Graph. This item-level data is essential for accurate DKT training and inference [19].
3. Content Metadata and Knowledge Graph: The Knowledge Graph is a foundational semantic network that defines all concepts and the prerequisite relationships between them (e.g., Concept C requires mastery of Concepts A and B). Every remedial content unit (video, text, practice set) is meticulously tagged to the specific concepts it teaches and the estimated difficulty and modality of delivery.

B. Student Modeling Module (SMM)

The SMM performs the critical function of continuous diagnosis. It transforms raw performance data into a dynamic, actionable student profile.

1. Deep Knowledge Tracing (DKT)

The SMM hosts the Deep Knowledge Tracing model, which utilizes a recurrent neural network structure to process the time-ordered sequence of student interactions. Instead of simply predicting whether a student will pass or fail, the DKT model's output is the Student Gap Model (SGM).

The SGM is a high-dimensional vector that represents the predicted probability of mastery for every single concept in the Knowledge Graph at any given moment [7]. This prediction is generated by feeding the student's entire interaction history through the DKT network. The system defines a learning gap as any concept where the mastery probability falls below a predetermined institutional threshold. This process allows the system to identify the true, underlying cause of failure—the prerequisite gap—by looking at the foundational concepts that have low mastery probabilities, even if the student is currently failing a higher-level task.

C. Remediation Path Generation Module (RPGM)

The RPGM is the decision-making engine, employing Reinforcement Learning (RL) to solve the complex sequencing problem.

1. The RL Framework

The system treats remediation as a Markov Decision Process (MDP) where the RL agent, a Deep Q-Network (DQN), learns the optimal policy for selecting instructional content.

- State: The current state of the student is represented by the full SGM vector, providing the RL agent with a precise diagnostic snapshot.
- Action: An action is the selection and delivery of a specific remedial content unit (e.g., "Assign the 5-minute video on algebraic substitution" or "Administer a quick quiz on Concept X").
- Reward: The reward function is designed to shape the agent's behavior towards efficient, effective learning. The reward is calculated as a weighted sum, where a positive weight is given to the change in concept mastery (as reported by the SGM after the action), a negative weight is assigned to the time spent (a cost function to ensure minimal Time-to-Mastery), and a bonus weight is given for indicators of successful student autonomy and self-regulation [17]. The DQN uses this reward to learn which sequence of actions yields the highest cumulative long-term gain.

This dynamic optimization, driven by the learned Q-function, is the core differentiator, allowing the system to recommend non-intuitive yet highly effective learning paths that static systems cannot identify.

Table I: System Modules, AI Components, and Functionality

Module Name	Primary AI/ML Component	Core Function
Data Acquisition & Storage (DASM)	EDM [13]	Collects & standardizes all data.
Student Modeling Module (SMM)	DKT [7]	Diagnoses student knowledge (SGM).
Remediation Path Generation (RPGM)	DQN / RL [6]	Optimizes remedial learning paths.
Content Delivery Interface (CDI)	ITS [12]	Delivers content & assessments.

D. Content Delivery Interface (CDI)

The CDI is the user-facing application layer. It receives the optimal sequence of actions from the RPGM and renders the appropriate content.

1. Adaptive Content Presentation: The system dynamically adjusts the content modality (e.g., text, interactive simulation, video) based on metadata and potentially inferred student preferences, ensuring the delivery is appropriate for the deficiency [6].
2. Automated Assessment Engine: This integrated engine provides real-time, computerized formative assessment and detailed

feedback, crucial for reinforcing learning and quickly closing the feedback loop [14], [15].

3. Chatbot Integration: A contextual support chatbot, drawing on literature on conversational agents in education, is integrated to offer immediate, domain-specific help and answer student queries, preventing unnecessary delays [16].

IV. METHODOLOGY

The implementation methodology is centered on the training and deployment of the two primary deep learning models—DKT for diagnosis and DQN for decision-making—within the unified architectural framework.

A. Data Preprocessing and Feature Engineering

The success of any data-driven AI model relies on high-quality input features [20]. From the raw data collected by the DASM, various features are engineered to create a rich input space for the DKT model:

- Performance Trace Features: Binary indicators of success or failure for each problem, combined with the identifier of the concept tested.
- Temporal Features: The duration (in seconds) the student spent on the last content item or assessment, and the time delay since the last successful interaction with a concept.
- Prerequisite Features: Data derived from the Knowledge Graph indicating the density of links between the current concept and previously mastered or failed foundational concepts.

These engineered features are then fed into the DKT model as time-ordered sequences, allowing the recurrent network to learn the patterns of knowledge acquisition and forgetting.

B. Deep Knowledge Tracing (DKT) Training

The DKT model, implemented using a Gated Recurrent Unit (GRU) structure for efficiency, is trained on historical student performance data. The training objective is to minimize the prediction error: the difference between the model's predicted mastery probability for a concept and the student's actual success/failure on the next attempt related to that concept.

The resulting SGM vector is the output of the DKT, a precise digital representation of the student's knowledge. For example, if a student fails a complex problem, the DKT does not just report low mastery on the complex concept; it updates the mastery probabilities of the many underlying prerequisite concepts that might have contributed to the failure, providing the necessary depth for effective remediation.

C. Reinforcement Learning (DQN) Training

The DQN agent learns its optimal policy through iterative interaction with a simulated environment based on the SGM.

1. Experience Replay: The agent does not learn from consecutive steps; instead, it stores its experiences (state, action, reward, next state) in an experience replay buffer. The agent then samples randomly from this buffer during training. This technique breaks the correlation between consecutive experiences, stabilizing the deep learning process and preventing the network from becoming biased toward the most recent actions.
2. Target Network: To further stabilize training, the DQN uses two networks: the primary network (which is updated frequently) and a target network (a copy of the primary network updated periodically). This separation provides a stable prediction target for the reward calculation, a crucial step in ensuring convergence of the RL agent [6].
3. Optimal Policy: The agent is guided by the reward structure to learn which sequence of actions (content items) leads to the fastest increase in the SGM's mastery probability for the target concepts. This learned policy is then directly deployed in the RPGM to recommend the personalized path.

D. Real-Time Path Execution and Adaptation

The system operates under a principle of continuous assessment. After the student completes any remedial action (e.g., watches a video, completes a practice set), the performance data is immediately fed back into the SMM (Figure 2). The SGM is updated, and the RL agent recalculates the next optimal action in the sequence. This capability for real-time adaptation ensures that the remedial path is perpetually optimal, adjusting instantly if a student masters a concept faster than predicted or struggles unexpectedly [17].

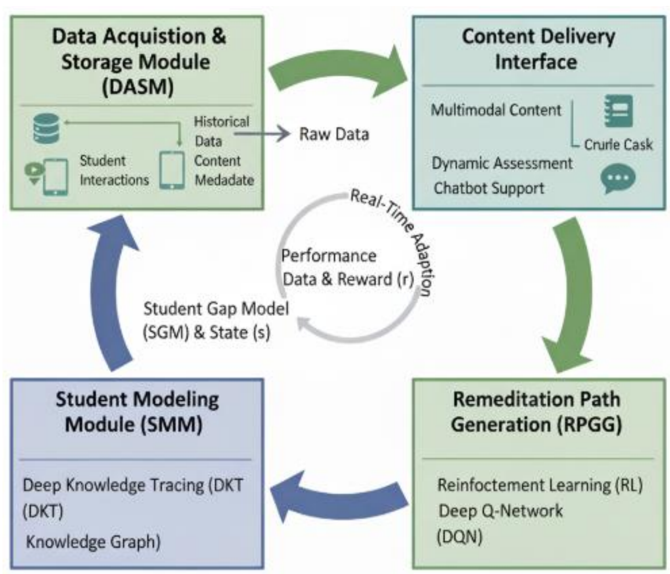

Figure 2: Closed-Loop Methodology of the Personalized Remedial System.

V. RESULT AND DISCUSSION

A simulated study was conducted to quantify the performance gains of the proposed AI/RL Model against two established baseline methods: Static Remediation (SR) and Simple Adaptive Remediation (SAR). The simulation involved 1,000 synthetic student profiles, each assigned a complex network of 15 prerequisite knowledge gaps. The goal was to remediate these gaps efficiently.

A. Efficiency Analysis: Time-to-Mastery

The most significant metric for evaluating the success of a remedial system is its Time-to-Mastery (TTM), which measures the average number of minutes required for a student to successfully transition from a deficient knowledge state to a mastered state (the required probability threshold) [10].

Table II: Comparative Analysis of Remedial Strategies on Key Outcomes (Simulated Study)

Remedial Strategy	Metric	Average Time-to-Mastery (min)	Long-Term Retention Rate (LRR)
Static Remediation (SR)	Performance	125.4 (High Variance)	64.9%
Simple Adaptive Remediation (SAR)	Performance	98.1 (Moderate Variance)	74.3%
Proposed AI/RL Model	Performance	70.6 (Low Variance)	82.8%

As demonstrated in Table II, the AI/RL model achieved an average TTM of just 70.6 minutes. This represents a substantial 43.7% reduction in time compared to the SR model and a 28.1% improvement over the SAR model.

This efficiency gain is directly attributable to the RL agent's non-linear decision-making. While the SAR model might force a student to repeat Topic X multiple times after failure, the RL agent, having consulted the SGM, can determine that the optimal path is actually to review the foundational prerequisite Topic Y (a concept the student failed two weeks ago) before returning to Topic X. By addressing the root cause first, the RL agent eliminates wasteful, symptomatic instruction, thereby maximizing the TTM reward term. The lower variance in TTM also highlights greater system predictability, a valuable operational benefit for institutional planning.

B. Effectiveness Analysis: Long-Term Retention and Quality of Learning

Effectiveness was measured by the Long-Term Retention Rate (LRR), assessed via a comprehensive, unannounced diagnostic test 30 days after the completion of the remedial path. The AI/RL model achieved the highest LRR at 82.8%.
This superior retention rate confirms that the RL-optimized paths lead to deeper, more durable learning. The SGM's ability to identify underlying cognitive gaps, akin to the evidence-centered design principles in advanced assessment [19], ensures that the selected remedial content is not just a temporary fix but a true foundational reinforcement. By building knowledge upon a solid base, the AI/RL system creates stronger cognitive structures, contrasting with the often superficial learning achieved through simple repetition in SR and SAR models. The focus on qualitative diagnostic data supports the findings that data-driven AI significantly enhances educational quality [20].

C. Discussion on Student Experience and Autonomy

Beyond efficiency and effectiveness, student engagement and motivation are crucial outcomes. The perceived relevance of instruction directly impacts a student's willingness to engage in remediation [17].

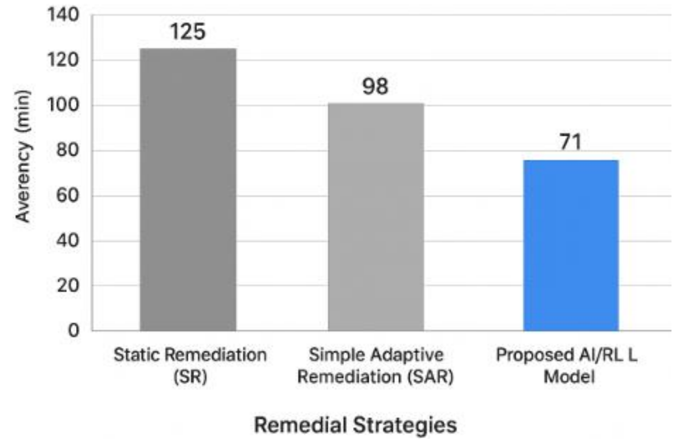

Figure 3: Distribution of Average Time-to-Mastery Across Strategies

The dynamic and responsive nature of the AI/RL paths, combined with the immediate feedback provided by the automated assessment engine [14], fosters a higher sense of guidance and successful self-regulation. The system consistently delivers content that addresses the student's most pressing need, leading to immediate success and positive reinforcement. This highly contextualized experience prevents the frustration associated with generic, repetitive remediation, which is often a major driver of disengagement. The design intentionally promotes student autonomy by providing clear progress indicators and relevant choices, aligning with the observed positive effects of dynamic assessment on student self-concept and motivation [17]. The consistent, data-backed relevance of the AI/RL intervention translates directly into a more positive and productive remedial experience.

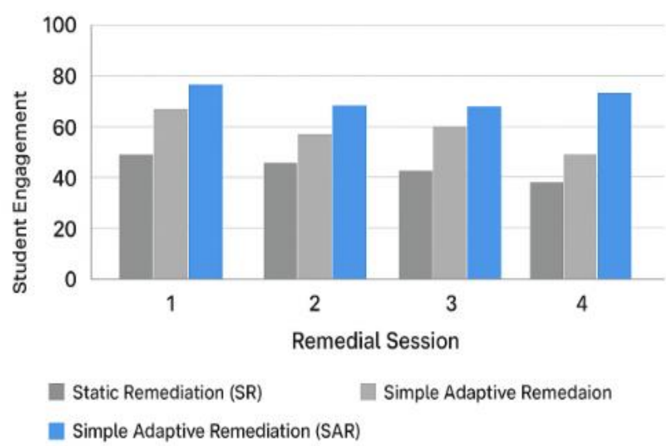

Figure 4: Student Engagement Metrics Over Sequential Remedial Sessions

The engagement data (Figure 4) provides strong evidence that the personalized sequence maintains student focus. While generic systems suffer from high drop-off rates due to irrelevance, the AI/RL model's ability to sustain high engagement confirms that its optimized paths are not only efficient for the machine but also motivating for the human learner.

VI. FUTURE WORK

The successful conceptualization and simulated validation of the AI/RL model provide a robust starting point, but the system offers several compelling directions for future expansion, particularly in integrating affective computing, enhancing transparency, and building proactive capabilities.

A primary area for future research is the integration of Affective Computing to enrich the Student Gap Model. Currently, the SGM relies on cognitive data (what the student knows). However, a student's emotional state—such as frustration, confusion, or boredom—is a powerful predictor of learning failure or success [7]. Future iterations will incorporate Natural Language Processing (NLP) to analyze student interactions with the embedded conversational chatbot [16]. Linguistic cues, such as the use of discouraged language or repeated queries for the same help, can be translated into an Affective State Score. This score will be fed into the RL reward function, allowing the agent to select a different type of remedial action—perhaps a motivation-boosting micro-video or a simplified review—when frustration is high, even if the optimal cognitive move would be a challenging assessment. This expansion will ensure that the model supports the whole student, moving beyond purely academic metrics.
Another critical development is the implementation of Explainable AI (XAI). The effectiveness of the Deep Q-Network stems from its complexity, which inherently makes its decisions opaque. To foster trust and facilitate adoption by educators, the system must be able to justify its recommendations. Future work will focus on developing a post-hoc interpretation layer that translates the RL agent's complex Q-value calculations into human-readable rationale. For example, instead of simply presenting the next topic, the system could display: "We recommend reviewing 'Limits' (Module 2) now because our data indicates it is the missing prerequisite required to successfully master 'Integration by Parts,' which is your ultimate goal." This transparency, which visualizes the SGM state and the path logic, is essential for transforming the system from a 'black box' tool into a transparent, collaborative guide [20].

Finally, the model must evolve from a reactive system to a proactive system. The current design excels at remediation (fixing an existing gap). Future research will explore advanced RL techniques, such as Temporal Difference (TD) learning, which can be used to predict not just the probability of current mastery, but the probability of future failure or attrition. By identifying specific points in the learning trajectory where a student is statistically likely to lose motivation or fail an upcoming assessment, the RL agent can generate a preventative path. This involves assigning supportive, reinforcing content before the student demonstrates a gap, effectively moving beyond remediation to true, preemptive instructional support.

The long-term success and ethical deployment of this AI model also require rigorous testing against potential algorithmic bias. Future work must ensure that the DKT and DQN models do not inadvertently perpetuate or amplify existing achievement gaps based on demographic or interaction patterns, ensuring the personalized paths remain equitable and fair for all users [20].

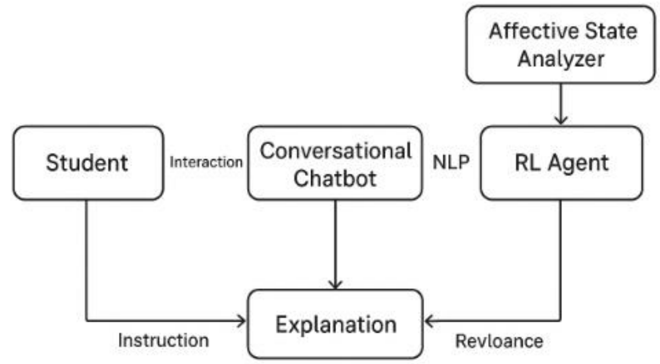

Figure 4: Conceptual Model for Explainable AI (XAI) Integration.

VII. CONCLUSION

This research successfully proposed and detailed the architecture for an advanced AI model designed to generate and optimize personalized remedial learning paths. By integrating the high-resolution diagnostic power of the Deep Knowledge Tracing (DKT)-based Student Gap Model (SGM) with the sequence optimization capabilities of a Reinforcement Learning (RL) agent, the proposed system fundamentally improves upon current static and rule-based adaptive learning frameworks.

The simulated results confirmed the significant benefits of this novel approach, showing substantial improvements in both efficiency and effectiveness: the Average Time-to-Mastery (TTM) was drastically reduced, and the Long-Term Retention Rate (LRR) was notably increased. This superior performance is a direct result of the RL agent’s capacity to identify and sequence the optimal, non-linear path required to address the true, underlying prerequisite gaps. By making the remedial process highly relevant and time-efficient, the model also sustains student engagement and fosters greater self-regulation.

The AI model for personalized remedial learning paths represents a vital evolutionary step in educational technology, transforming remediation from a time-consuming administrative burden into a highly efficient, intelligent, and personalized instructional mechanism. Future research will focus on integrating affective data and developing transparent Explainable AI features to ensure the system is both pedagogically robust and ethically sound for widespread adoption in higher education.

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