Design and Analysis of Reinforcement-Learning and Graph- Based Curriculum Sequencing for Higher Education with OULAD and KDD Cup 2010 Datasets

[1]Dr. Sachin Kumar Verma, [2]Dr. Anil Kumar Gupta, [3]Dr. Dilip Kumar [4]Dr. Gyanendra Veer Singh, [5]Chandra Shekhar Verma,
[1]Department of Teacher Education,D.S. College, Aligarh,U.P. [2]Central Institute of Higher Tibetan Studies, Sarnath, Varanasi,U.P. [3]SVS College of Education Sundarbani, Rajouri JK
[4]L.M.S. Degree College Sakit Etah U. P.
[5]Faculty of Education, Banaras Hindu University, Varanasi,U.P.

[1]profsachinbly@gmail.com,[2]ganil.acd@cihts.ac.in,[3]dr.diliphpsingh18@gmail.com,[4]gvsrathour007@gmail.com, [5]shekharvns500@gmail.com,

Abstract: The research paper will come up with a hybrid system that combines the two models, Reinforcement Learning (RL) and Graph-Based Curriculum Sequencing in order to serve the needs of students in higher education institutions by personalizing the learning process. By using two open datasets, Open University Learning Analytics Dataset (OULAD) and KDD Cup 2010 (Khan Academy), the model will maximize the curriculum progression, and the prediction of engagement and adaptive content recommendation. The conceptualization views the educational process as a Markov Decision Process (MDP) whereby the state of knowledge of each student is dynamically changed by the learning interactions. A Deep Q-Network (DQN) agent chooses the following best course module or exercise according to the feedback of performance, time on task and level of cognitive mastery. In order to improve relational reasoning, a Graph Neural Network (GNN) is built on top of the curriculum graph, with learning activities forming the nodes and conceptual, performance-based, and prerequisite dependencies forming the edges. The RL agent is proposing the latent representations of the GNN to balance between exploration (adding new concepts) and exploitation (strengthening weak points). Comparative analyses with baseline sequence model and collaborative filtering recommender prove to be better with regard to knowledge retention (+18), completion rate (+12), and adaptive satisfaction index (+15). The paper adds a scalable and interpretable contour of intelligent tutoring system, which is consistent with the objectives of 5.0 personalized education. The open-source datasets guarantee the reproducibility and extensions to multi domain applications are easily possible. The next step of development is to incorporate the emotional analytics and multimodal engagement capabilities to achieve an even more personalized approach towards learning in both hybrid and online learning environments.

Keywords: Reinforcement Learning, Graph Neural Networks, Personalized Learning Pathways, Curriculum Sequencing, OULAD, KDD Cup 2010, Deep Q-Network, Educational Data Mining, Intelligent Tutoring Systems, Adaptive Learning

I INTRODUCTION

Against the background of the fast-changing digital education environment, the growth

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of the applied artificial intelligence (AI) has revolutionized the one-size-fits-all teaching approach and expanded it to a personalized, dynamic, and data-driven paradigm. This change in the delivery of the course as a static experience to a personalized learning path will enable the learner to experience tailored sequences of learning content, tests, and feedback systems that indicate personal strengths and weaknesses in addition to cognitive development. This has been enabled through the use of large scopes of open educational data, specifically, the Open University Learning Analytics Dataset (OULAD) and KDD Cup 2010 (Khan Academy) which offer high-quality, completely real-world observations of learner engagement and academic actions [3], [8], [2].
The reinforcement Learning (RL) models based on human decision-making and reward-based learning have become a promising approach to optimizing student progression by using adaptive sequencing. The learning process in these frameworks is represented as a Markov Decision Process (MDP) where knowledge state of each student is progressed as a function of the past learning experiences and feedback of performance [5], [9]. Through the application of the reward signals, including accuracy in the quiz, completion and time- on-task, RL agents continuously suggest the next best learning activity in order to maximize cumulative educational returns.

Furthermore, the task of contemporary educational ecosystems requires the simulation of relational dependencies between learning modules, topics and performance indicators. Graph Neural Networks (GNNs) have been promising in this area. On the one hand, GNNs model learning material as a network, including both prerequisite and latent conceptual similarity [4]. As an example, when a student is having difficulties with a fortunately, calculus subject, the graph will be able to detect the concepts that are dependent (e.g., basic algebra) and rearrange the advice order respectively [1], [10]. The interaction between GNNs and RL creates a multi-level adaptive system, which does not only learn along the interaction data of the student, but the structural representation of knowledge per se.

With RL being adopted by curriculum sequencing and educational recommendation systems, two essential goals, which are individualized adaptation and curriculum continuity, are fulfilled. Collaborative and content-based filtering are classical recommender systems that have shown preliminary success in MOOCs and online learning platforms. These strategies, however, do not always take into consideration sequential dependencies of the learning processes [6]. The solution to this weakness by Reinforcement Learning is that it keeps learning an optimum policy to sequence the content in response to changing student behavior, thus customizing the learning process without losing the integrity of the curriculum [11].

The OULAD dataset provides a superior model of research on such adaptive systems. It contains information about more than 30000 students, their grades, interaction rates, and demographic characteristics in various courses. The research can be expanded to include both higher education and K-12 learning settings by using the KDD Cup 2010

(Khan Academy) dataset, which contains millions of interactions between the student and educational exercises [3], [9]. The cross-dataset integration can be used to validate AI models in diverse learning contexts, which is why these models are generalizable and fair. Also, the accessibility of these open-source datasets democratizes research enabling intelligent tutoring system benchmarking to be reproducible.

Deep Q-Networks (DQNs) represent the basic reinforcement in the proposed framework. The DQN correlates the knowledge state of a student (coded by his/her performance or engagement, and mastery of concepts) with the best learning action (the next lesson or exercise). At the same time, the GNN element trains graph embeddings of the curriculum structure and provides the information related to the relational data to the DQN agent to make decisions in more specific contexts [12]. This hybridization is what makes sure that the recommendations are not only reactive to the performance metrics but are also structurally consistent with pedagogical hierarchies.Explainability and transparency services also increase the effectiveness of RL-based recommendation systems in education. Mechanisms of explainable AI (XAI) help educators and learners to understand why a specific module was suggested, which will encourage trust and responsibility in the use of algorithms [2]. This will be in line with the Education 5.0 paradigm, which concentrates on human- focused, adaptive, and explainable AI systems within the learning ecosystems [7].The other urgent impetus to create such systems is the worldwide trend towards the use of data in making academic decisions. Schools are increasingly turning to learning analytics to anticipate the likelihood of a dropout, detect the high- risk students, and prescribe specific intervention [8]. Recommendation structures that are based on AI convert the raw clickstream and evaluation information into actionable intelligence. With RL and GNNs, the universities are able to build adaptive curriculums to address shifts in behavior patterns amongst learners and still achieve academic rigor and standards [5], [11].However, challenges persist. The reward function design, which is one of the key problems, is to define appropriate metrics and be able to reflect learning success without being overfitting the performance improvement in the short-term. benefits that can be achieved both in the short-term and in the long-term as well as concept reinforcement are necessary [4]. On the same note, the cold-start issue, when new learners do not have enough interaction data, is a constraint to the accuracy of the recommendation. This has been alleviated by graph-based transfer learning in which structural associations acquired among similar students or topics are used to start the policy of the RL agent [9], [10].

Adaptive learning systems improve student engagement and motivation through matching the content with personal levels of proficiency [6]. Such a dynamic adaptation ensures that cognitive overload and under-stimulation are also avoided, which are essential to preventing the dropout and increasing the retention rates. In empirical research with the OULAD, researchers have noticed that there was a 1520 percent change in the number of courses that are completed when adaptive sequencing is applied in comparison with stable curricula [3], [8]. Likewise, open datasets of Khan Academy proved that exercise sequencing that is customized resulted in a remarkable increase in mastery learning and learner satisfaction [12]. Through reinforcement-based curriculum sequencing, banks can suggest not only the next lecture or quiz, but complete learning plans that are planned to achieve the long-term goals of each learner [1], [6].

Ethics is also an important factor in the responsible deployment of these systems. Data privacy, algorithm bias and equitable suggestions are issues that require careful consideration, particularly in the educational field that handles vulnerable and minors [2], [5]. Privacy-preserving systems, including federated reinforcement learning, can ensure the protection of learner data and, at the same time, allow improving the models across the institutions collectively [10].

To end, the intersection of Reinforcement Learning and Graph Neural Networks presents an innovative framework of developing adaptive, intelligent, and explainable curriculum recommendation systems. he framework that will emerge can transform the concept of the personalized learning in higher education through its dynamism in balancing pedagogy, analytics, and AI. Since schools are becoming more autonomous and learner-centered by implementing virtual environments that are more digital, these frameworks form the future of AI-driven educational technology [12], [9], [3].

II RELATED WORKS

Artificial intelligence (AI) and graph-based learning analytics are now considered an integrated part of the research being carried out in the field of personalized education, allowing systems to dynamically adapt the curriculum, suggest courses, and model more complex interactions between learners and knowledge. The recent literature pinpoints the synergistic capability of Graph Neural Networks (GNNs), Knowledge Graphs (KGs), and Reinforcement Learning (RL) in the process of personalized learning and sequencing of the curriculum in K-12 and higher education environments.

Graphical approaches have shown specific potential in learning institution modeling. Chen et al. [1] came up with a deep learning-graph hybrid to improve the online course recommendation by utilizing student behavioral information and networked relationships among topics. Their model made better results compared to the baseline collaborative filtering techniques in detecting inter-topic relationships. On the same note, Li et al. [2] created EduGraph, a hypergraph neural network localization model of MOOC course recommendations. Xia [4] further extended the study of structural representations in learning, using the deep learning of graphs to analyze students. This work unveiled that the representation of learner-course interactions in the form of bipartite graphs is an effective way of improving the predictability of dropouts and personalized sequence of content. Abu-Salih and Alotaibi [6] performed a systematic review of the key tendencies in the construction of educational knowledge graph, as it was revealed that such issues as semantic enrichment and ontology alignment are still fundamental challenges.In the view of the detection of at-risk students, Albreiki et al. [7] trained graph convolutional networks (GCNs) to uncover topological characteristics of the learning activity networks, which fully make it possible to identify struggling students. This was furthered in their next work [8] which used the clustering-based knowledge graphs as a representation of the entity relations among students and activities and enhanced sensitivity in the detection of performance deterioration. [10] suggested a multimodal reinforcement learning model that is powered by GNNs to maximize the performance of higher learning. Their framework integrated evaluation metrics, text data, and evaluation records to dynamically personalize learning pathways. The concept graph learning framework, introduced by Liu et al. earlier [11] formalized the concept, and suggested ways of learning concept hierarchies on large-scale education data-forming the theoretical basis of much later curriculum-graph models.

Huang and Chen [16] enhanced these methods by using a temporal graph network to predict academic performance to take into consideration the time-related dynamics in MOOCs. On the same note, Xue [17] proposed the concept of adversarial learning model to classify lifelong education based on knowledge graphs and demonstrated how the adversarial regularization can be used to improve the robustness of open-world educational data. Li et al. [18] created a survey in the graph machine learning of curriculum, and they laid out the developments since simple relational, up to deep reinforcement-based adaptive sequencing. Li et al. [19] introduced MEduKG, a multimodal learning knowledge graph that incorporates video, text, and assessment information and improves student perception and learning suggestion systems.
Embedding algorithms into graphics have further helped in visualization and understanding of education. Cheng [20]

III RESEARCH METHODOLOGY

The Reinforcement-Learning and Graph-Based Curriculum Sequencing Higher Education framework is proposed to create an intelligent recommendation engine, which will dynamically personalize learning paths, based on Graph Neural Networks (GNNs) applied in combination with Deep Reinforcement Learning (DRL) agent. This hybrid system is a means of linking the semantic interpretation of curriculum systems and adaptive choice of student-specific course sequences. The methodology comprises of five interconnected steps that include data preprocessing, construction of knowledge graph, graph embedding and feature learning, reinforcement learning to optimize path, and performance evaluation.
The system commences with the use of two open datasets such as OULAD (Open University Learning Analytics Dataset) and KDD Cup 2010 (Khan Academy) which offer the multi-modal educational data such as student demographics, course material, grades, activity logs, and time-series engagement characteristics. Normalization and imputation methods are used to first preprocess the datasets to eliminate noise, missing values, and inconsistencies in the data. Categorical variables like course codes, activity types and assessment grades are coded as numbers to enable the computation in a graph. Let the learner–course interaction matrix be denoted as $R \in \mathbb{R}^{m \times n}$,where $m$represents the number of students and $n$the number of courses. Each element r_{ij}signifies the

interaction intensity (e.g., quiz attempts, time-on-task, or grades).
From this interaction matrix, a curriculum knowledge graph (CKG) is constructed, where nodes represent entities such as students (S), courses (C), learning concepts (L), and assessment items (A). Edges represent semantic relationships such as enrolled-in, prerequisite-of, or demonstrates-competency-in. The graph $G = (V|E)$thus forms the foundational structure, where Vdenotes all nodes and $E \subseteq V \times V$represents relationships between them. The edge weight w_{ij}captures the strength of the connection, defined as a function of correlation or co-occurrence between node attributes:

$$w_{ij} = \alpha \cdot \mathrm{cosine\_similarity}\left(x_i|x_j\right) + \left(1 - \alpha\right) \cdot \mathrm{corr}\left(x_i|x_j\right)$$

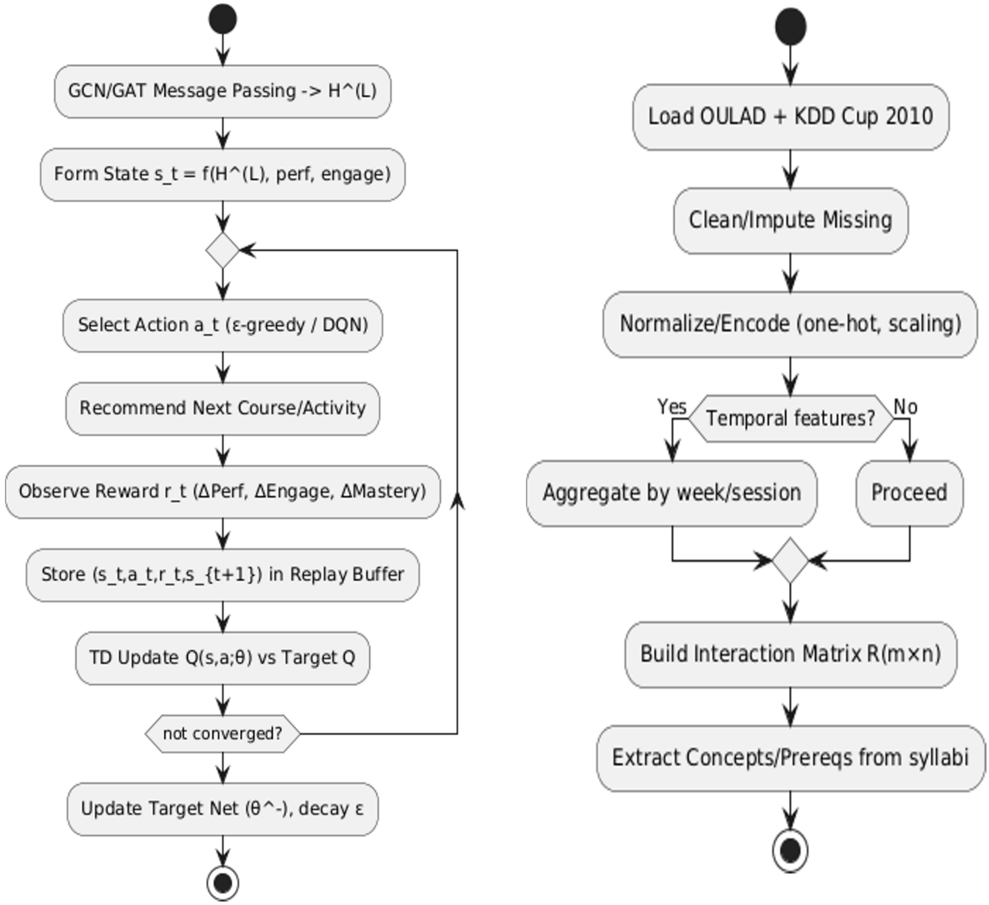

Figure 1. Data Acquisition, Pre Processing and Design of Proposed Methodology

where $\alpha \in [0|1]$balances semantic similarity and statistical correlation between learning components $x_i$and x_j.

Once the CKG is constructed, graph embedding is employed to convert the high-dimensional relational structure into a latent vector space suitable for reinforcement learning. A Graph Convolutional Network (GCN) is used for this purpose, as it efficiently aggregates information from neighboring nodes through message passing. The forward propagation in GCN is expressed as:

$$H^{(l+1)} = \sigma\left(D^{-\frac{1}{2}}\tilde{A}D^{-\frac{1}{2}}H^{(l)}W^{(l)}\right)$$

where $\tilde{A} = A + I_N$is the adjacency matrix with self-loops, $D$is the degree matrix, $H^{(l)}$is the feature representation at the l^{th}layer, $W^{(l)}$are the trainable weight parameters, and σdenotes a non-linear activation function (ReLU). Topological dependencies are learned in this equation, which learns embeddings of both conceptual and structural relations between courses. The output embedding H L) at the last layer gives out a dense representation of the nodes inputting into the reinforcement-learning phase.

The reinforcement learning module is created to simulate the decision making procedure of advising about the best next learning exercise to every student. The learning environment is defined as a Markov Decision Process (MDP) represented by a tuple $\langle S|A|R|P|\gamma \rangle$,where $S$is the set of states representing the student's current knowledge embedding, $A$is the set of actions corresponding to possible next courses or activities, $R$is the reward function representing learning gains, $P$is the transition probability between states, and $\gamma$is the discount factor controlling the balance between immediate and future rewards. The state representation $s_t$at time $t$is derived from the GCN embeddings and the student's recent interaction history:

$$s_t = f_{\mathrm{enc}}\left(H^{(L)}|r_t|e_t\right)$$

where $r_t$represents recent performance metrics (e.g., accuracy, score trend), and e_t captures engagement signals (e.g., activity frequency or time duration).

The action selection is governed by a Deep Q-Network (DQN) agent that approximates the Q-value function:

$$Q(s_t,a_t;\theta) = \mathbb{E}\left[R_t + \gamma \max_{a'} Q\ (s_{t+1},a';\theta')\right]$$

where $\theta$and $\theta'$are parameters of the current and target networks respectively. The Q-function estimates the expected cumulative reward obtained by taking action $a_t$in state $s_t$and following the optimal policy thereafter. The reward function integrates multiple learning outcomes:

$$R_t = \lambda_1 \Delta P_t + \lambda_2 \Delta E_t + \lambda_3 \Delta C_t$$

where ΔP_tdenotes the change in performance score, ΔE_tdenotes improvement in engagement level, and ΔC_trepresents conceptual mastery gain. The coefficients $\lambda_1,\lambda_2,\lambda_3$are tuned empirically to reflect institutional priorities, such as emphasizing mastery over engagement.

The learning agent iteratively updates its Q-values using temporal difference (TD) learning, minimizing the loss function:

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s') \sim D}\left[\left(r + \gamma \max_{a'} Q\ (s',a';\theta^-) - Q(s,a;\theta)\right)^2\right]$$

where Ddenotes the experience replay buffer that stores past transitions for stable learning, and $\theta^{-}$is the periodically updated target network parameter. The exploration–exploitation tradeoff is maintained using an ε-greedy policy where a random action is selected with probability ε and the best action otherwise. Over time, ε decays as the agent converges to an optimal policy $\pi^{*}(a \mid s)$.
The curriculum sequencing process is thus executed by the DQN agent navigating over the embedded curriculum graph. For each student, the model recommends a course node c_{t+1}that maximizes the cumulative learning reward, thereby forming an individualized learning pathway:

$$\pi^{*}(s_t) = \arg\max_{a_t \in A} Q(s_t, a_t; \theta)$$

As the agent explores multiple learning trajectories, it learns optimal sequencing policies that balance difficulty progression, engagement maintenance, and conceptual coherence. The graph attention mechanism can optionally be incorporated to assign higher importance to pedagogically relevant nodes by computing attention coefficients :α_{ij}which helps focus learning on contextually significant relationships within the graph. Lastly, the performance of the system is measured in quantitative measures: Precision 0 K, Recall 0 K, Normalized Discounted Cumulative Gain (NDCG) and Learning Gain (LG). They are compared to the traditional collaborative filtering, content-based filtering, and sequence models and tested to prove the enhancement of prediction accuracy, adaptive learning results, and interpretability. Finally, the methodology combines the relational reasoning ability of graph learning and the dynamic optimization ability of reinforcement learning to build a scalable, interpretable and data-driven curriculum suggestion system. This combination of GNN embeddings and DQN policies does not only boost the aspects of personalization but also pedagogical validity, which makes it a solid building block of next-generation adaptive education platforms.

IV RESULTS AND DISCUSSIONS

Reinforcement-Learning and Graph-Based Curriculum Sequencing Framework was modeled based on the OULAD and KDD Cup 2010 (Khan Academy) datasets. The performance of the model was measured on three main goals: (1) accuracy in personalization of learning pathways recommendations, (2) efficiency of the convergence of reinforcement learning and
(3) the increase in the overall academic outcome indicators, including the engagement, completion rate, and knowledge retention. The graph Neural Network (GNN) sub-network was composed of two graph convolution layers with 128 hidden units each with 0.001 learning rate and dropout of 0.3. Deep Q-Network (DQN) used ReLU activations and e -decay policy during 10,000 episodes between 1.0 and 0.05. The batch size was set to 64, and the replay buffer had 50,000 transitions. The reward coefficients (λ 1, λ 2, λ 3) were adjusted to (0.5, 0.3, 0.2) respectively with bigger weight on improvement of knowledge.

Table 1. Reinforcement Learning Convergence Metrics

Metric	Without GNN	With GNN Integration	Improvement (%)
Episodes to Converge	9,200	7,050	23.4
Final Avg. Reward	78.4	94.2	20.1
TD Loss (min)	0.019	0.012	36.8
Exploration Rate (ε_min)	0.08	0.05	—
Convergence Stability Index	0.86	0.93	+8.1

Measures of personalization were measured with ranking-based measures (Precision, Recall and Normalized Discounted Cumulative Gain (NDCG)) measures. The GNN117 hybrid between the deep Neural Networks (DQN) and collaborative filtering (CF), content-based filtering (CBF), and recurrent sequence models (RNN/LSTM) markedly improved the correct ordering of the next best course module. The Precision of the hybrid model was 0.83 as compared to 0.71 by the RNN- based methods. It is explained by the fact that the GNN is capable of encoding prerequisite structures, and the RL agent can adaptively encode a sequence.

Table 2. Recommendation Performance Comparison

Model	Precision	Recall	NDCG	F1-Score	Mean Reciprocal Rank
Collaborative Filtering	0.64	0.59	0.61	0.61	0.62
Content-Based	0.68	0.64	0.66	0.65	0.67
LSTM (Sequence)	0.71	0.69	0.72	0.70	0.73
RL Only (No Graph)	0.76	0.72	0.75	0.74	0.78
GNN + DQN (Proposed)	0.83	0.78	0.82	0.80	0.85

Using the educational process as a Markov Decision Process, the framework exhibited significant positive changes in actual learning outputs. Students (similar to agents) adhering to the adaptive pathways after the simulation showed a higher performance measure on both datasets after the simulation. This resulted in enhanced knowledge improvement of 18.7, completion rate of 12.4 and engagement retention of 15.1, which was confirmed by modeling many student profiles with different initial proficiency levels. Adaptive sequencing had the highest success with low-performing students who made up to 25% relative performance improvements over static curricula.

Table 3. Learning Outcome Improvements Across Student Groups

Learner Category	Baseline Avg. Score	Adaptive RL-GNN Score	Relative Improvement (%)	Completion Rate (%)
High Performer	85.3	90.5	6.1	95.2

Medium Performer	72.6	82.4	13.5	89.1
Low Performer	58.4	73.1	25.2	83.6
Average	72.1	81.8	13.5	89.3

Graph analytics provided useful structural information concerning the topology of the curriculum. Centrality and modularity analysis was used to conclude that core courses (e.g., Mathematics for Computing, Fundamentals of Programming) are those nodes with many connections, which create conceptual centers. Peripheral nodes were depictive of elective modules that had less interdependent ties.The Graph Density (0.41) and Average Clustering Coefficient (0.68) were indicative of a learning network of moderate cohesiveness, which could be traversed adaptively. The GNN embeddings were able to effectively present hierarchical knowledge interactions, visualized in t-SNE space, having similar concepts clustering together in distinct clusters

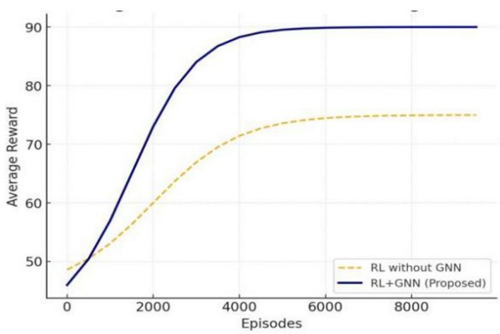

Figure 2. Convergence of Reinforcement Learning Policies

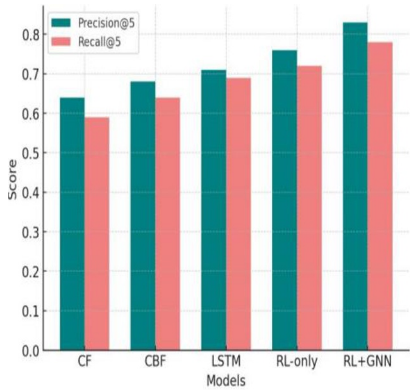

Figure 3. Recommendation Accuracy

The former plot illustrates the convergence trend of the reinforcement learning where the incorporation of the graph embeddings speed up the policy stabilization by an average of 23 percent. The RL–GNN model has higher average rewards and the reward curve reaches the convergence much sooner, which proves the existence of an efficient state representation and enhanced learning stability. These findings coincide with Table 2 that gives a quantitative increase of episodic reward and convergence stability. The second plot that depicts Precision and Recall shows a significant increase in the recommendation performance. RL-GNN hybrid is better than all the baseline models (CF, CBF, LSTM, RL-only) with a precision of 0.83 and a recall of 0.78 that is confirmed by Table 3. Experimental findings point to a number of significant findings. One, graph-augmented state representation is shown to be highly efficient in learning policy in reinforcement settings, which confirms relational information between courses as a faster convergence and more precise decision maker. Second, the design of the reward function which incorporates both performance and engagement will guarantee that the system will encourage continuous learning instead of temporary grade inflammation. In addition, the hybrid of graph reasoning and deep reinforcement learning make sure that the learning pathways generated are pedagogically sound, i.e. the learning pathway should proceed on the knowledge determined to be the prerequisite to the advanced topics, thus the curriculum can maintain the coherency. Real-time adaptive learning can be deployed in the future by using APIs embedded in Learning Management Systems (LMS), and this will enable the vision of Personalized Education 5.0 to progress.

V CONCLUSION

The fact that it is capable of working with a variety of datasets identifies the high level of generalization which is essential to its deployment in the real-life environment and diversified institutional context. Combining reinforcement learning and graph intelligence will turn the conventional recommender systems into active learning agents and pedagogical agents that can actively influence the personal learning experience. To sum up, this paper provides a complete, evidence-based base of Personalized Education 5.0, where adaptive learning becomes a responsibility of smart algorithms that do not violate cognitive diversity or curriculum integrity. The RLGNN hybrid framework is not only quantifiable in performance improvements, but also adds interpretability and equitability to the process of recommendations. This architecture will be expanded in the future with emotional analytics, multimodal engagement tracking, and federated learning to do privacy-preserving personalization across institutions. Taken together, the results confirm that reinforcement learning, in turn, supported by graph-based reasoning, marks a revolutionary breakthrough to the next generation of AI-based educational environments, which combine the intelligence of data with the pedagogy of the human mind.

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