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AI-Driven Dynamic Curriculum Design with a Hybrid of Reinforcement Learning and Evolutionary Algorithms

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Abstract

The traditional curriculum design frameworks are rigid, which cannot meet the diversified and dynamic learning needs of students and which will not promote students' engagement, knowledge retention, and academic performance optimally. The proposed framework in this paper is a Dynamic Curriculum Design Framework based on Adaptive Intelligent Learning Environments (AILE), which is a combination of Reinforcement Learning (RL) and Evolutionary Algorithms (EA) to provide adaptive, personalized, and optimized learning pathways. The proposed hybrid framework consists of the following five stages: data acquisition, data preprocessing, learner profiling, RL-based curriculum adaptation, and evolutionary optimization. The RL module uses Q-value optimization to adjust curriculum policies during real-time interaction with the learner, and the EA module uses the genetic algorithm to optimize curriculum structures to prevent local optima stagnation by applying selection, crossover, and mutation operations. Personalization accuracy is further improved by the use of min-max normalization and clustering-based learner profiling. The proposed Hybrid RL-EA Framework was evaluated experimentally with educational datasets collected from intelligent learning platforms and was found to significantly outperform all the baseline systems. The curriculum adaptation accuracy was 95.8%, the engagement rate was 93.4%, the efficiency of retaining the course was 91.7%, the course completion rate was 95.2%, academic improvements were 44.1%, and the learning efficiency was 94.8%. Convergence is achieved in 71 iterations, while reduced configurations require 137 iterations. Ablation studies were performed that demonstrated that all components play a critical role in overall performance. The proposed framework provides a scalable and efficient way forward for next-generation, intelligent educational platforms, with measurably better personalization, engagement, and learning results, compared to traditional e-learning and isolated AI-based curriculum platforms.

Keywords: Adaptive Curriculum Design, Reinforcement Learning, Evolutionary Algorithms, Personalized Learning, Intelligent Educational Systems.

1. Introduction

Many educational systems today have experienced a radical change due to the fast development of Artificial Intelligence (AI) in learning environments, which now allow for intelligent and adaptive learning environments for personalized learning [1]. Traditional curriculum design methods are mostly passive and fixed structure, which offer the same curriculum content to all learners regardless of their learning pace, cognitive level, interest, and academic performance [6][8]. These traditional methods tend to be inflexible and do not meet the diversity of student learning behaviors and changing educational needs. As the online learning platform evolves and the digital classroom and intelligent tutoring system become increasingly developed, the demand for dynamic curricula to continuously adjust learning pathways is increasing. Machine learning, and specifically Reinforcement Learning (RL), has recently gained a lot of interest in the field of education, specifically for solving educational optimization problem. Reinforcement Learning can be used to maximize long-term returns such as student engagement, academic success, and knowledge retention by having intelligent systems learn optimal decision-making strategies by interacting with the learning environment. However, RL-based curriculum systems could be plagued with slow convergence, getting stuck at a local optimum, and requiring a lot of computation for a massive learning data set. To address these issues, some methods of natural evolution, specifically Evolutionary Algorithms (EAs), such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) emerged. These algorithms can efficiently search vast search spaces and acquire near-optimal curriculum structures. The fusion of Reinforcement Learning and Evolutionary Algorithms is an adaptive and efficient global optimization of curriculum design which is an intelligent approach.

The main purpose of this research is to propose an AI-based dynamic curriculum design framework based on Reinforcement Learning and Evolutionary Algorithms, which incorporates a hybrid method to devise the best personalized curriculum paths. The proposed system is designed to process the learners' behavior, learning performance, learning preferences, students' engagement, and make adaptive curriculum structures, which will adapt dynamically with students' learning progress. The study also aims to maximize learning outcomes, including learning efficiency, knowledge retention, student satisfaction, and academic achievement, and to enhance the curriculum sequencing, learning content suggestions, and adaptability of teaching to student needs. Further, the framework aims to break the rigid curriculum and make intelligent decisions in the modern digital education platform [23],[25].

For example, although AI has been introduced in the field of education, there are still a number of weaknesses in the current curriculum design systems [19]. Most of the traditional adaptive learning models are mainly based on static rule-based learning models, which are not flexible enough or personalized enough for real-time learning. Existing machine learning-based curriculum systems often focus only on prediction accuracy without addressing curriculum optimization and long-term learning progression [20][24]. While Reinforcement Learning has been explored for intelligent tutoring systems, many of the studies are not scalable, converge slowly, and do not examine learning paths enough. Similarly, Educational Optimization problems have been tackled in isolation with Evolutionary Algorithms, but their application with a sequential decision making model is not widely used. Very few of the current hybrid AI systems consider both the two processes (adaptation and optimization) simultaneously and in a single curriculum design architecture [16][26]. Furthermore, most of the studies reviewed have not included extensive measures of engagement, adaptive curriculum modification and learning efficiency in multiple educational contexts. Therefore, an AI-powered solution with adaptive intelligence and optimization algorithms for scalable, individualized curriculum is needed.

The hypothesis is that applying Reinforcement Learning (RL) and Evolutionary Algorithms (EA) methodologies will be able to greatly improve the adaptability of the curriculum, personalization of learning, engagement of the learners and academic outcomes as opposed to the static and one-model approach of traditional research in the field of AI and curriculum design [2][18]. We envisioned the hybrid approach to be better able to optimize curriculum sequencing and learning content selection by combining both exploration and exploitation strategies with global optimization strategies. Moreover, it is hypothesized that the proposed model can attain higher learning efficiency, quicker adaptation to students' behavior, better retention of knowledge, and better convergence performance compared with the standalone Reinforcement Learning systems, which typically suffer from computational limits.

A new hybrid framework is presented in this research to design a dynamic curriculum using AI techniques: a hybrid of Reinforcement Learning and evolutionary algorithms to create adaptive and optimized learning trajectories[27]. The proposed model contributes to the development of intelligent learning systems and the continuous modification of the curriculum based on the real feedback that students can give and the analysis of the student's performance. In this study, the balance of the adaptability of the curriculum and the efficiency of curriculum optimization is also presented with the use of an intelligent decision-making mechanism. A significant one is the development of a scalable architecture to support personalization of learning in a wide variety of educational data and for a variety of learner types. In addition, a comprehensive performance assessment system based on the education indicators is introduced in the proposed framework, which includes the indicators of 'engagement rate', 'learning efficiency', 'convergence adaption', 'learning improvement', 'convergence stability' and 'accuracy of convergence optimization'. The study also establishes the groundwork for future development of intelligent education platforms, providing a solid foundation for the development of intelligent curriculum management and personalized digital education system.

This article consists of six main sections. The Introduction offers an overview of the background, research aims, problem statement, hypothesis, and contributions of the proposed framework of dynamic curriculum design based on AI. The Literature Review, presented in Section 2, is a review of existing research and application of adaptive learning and reinforcement learning, evolutionary algorithms and intelligent education systems. In section 3, proposed Hybrid RL-EA framework is explained which includes the data pre-processing, learner profiling, reinforcement learning adaptation, evolutionary optimization and system implementation. For the Results as presented in Section 4, the experimental results, performance evaluation, and comparative analysis are presented. The results in Section 5 are discussed in the Discussion in Section 5. The overall findings and the contributions of the proposed framework are summarized in the last section, the Conclusion, in the end.

2. Literature review

The application of AI in education has revolutionized the development and delivery of curricula and personalized learning. The application of AI-based approaches to customize learning processes to match the needs of any particular student has proven to be quite promising, particularly for higher education [1, 7]. Data can be used in the design of curriculum to enable an institution to adopt an approach beyond "content delivery" to one that is responsive and focused on the student and that caters for the evolving need of technology [3], [13].

AI-based adaptive learning systems are quickly gaining popularity for their ability to dynamically adjust the content of instruction, monitor learning progress and detect learning styles through machine learning [9] and [17]. The systems are designed to improve the engagement and motivation of the learners by offering personalized learning experiences: one of the key components in both online and offline learning, has been proven to be vital for learning. The ability of personalized learning to be scaled up by the use of platforms that leverage intelligent algorithms to make mass customization of learning trajectories possible [10] has also increased.

Reinforcement learning (RL) is an especially intriguing method for curriculum optimization, as it enables systems to figure out how to optimize curriculum sequences by trial and error and feedback based on reward. The effectiveness of RL-based ITS that can deliver adaptive feedback and real-time feedback has been proved in relation to learning performance [21]. Policy-based RL models have also been applied in complex system stability problems and system optimisation problems, and have been found to be robust in dynamic environments [14].

It can be further enriched by the Introduction of game elements and artificial intelligence which can keep the motivation and engagement of the students for the learning process [11]. The Adaptive Intelligence Learning Framework (AILF) is a functional optimization model which represents the relationship between the adaptive input and the measurable educational outcome [15]. Besides, there is a need for responsiveness in dynamic learning environments that can be realized by applying context-aware adaptive learning models [22]. A fundamental challenge is the ethical transparency and fairness of such systems that are now being used on a large scale in institutions [4].

3. Methods

Research Framework

The proposed research work is to develop an AI based adaptive curriculum design framework to design an adaptive personalised curriculum using Reinforcement Learning (RL) and evolutionary algorithms (EA). The methodology is developed to constantly process the interaction between learners, optimize teaching timetable and dynamically adjust the teaching content according to learners' performance, engagement and cognitive development.

The entire architecture consists of five major stages: data acquisition, data preprocessing, learner profiling, curriculum adaptation via reinforcement learning and evolutionary optimization. The system continuously refines and suggests curriculum based on intelligent feedback and strategies to enhance the effectiveness of the curriculum and maximize learner satisfaction.

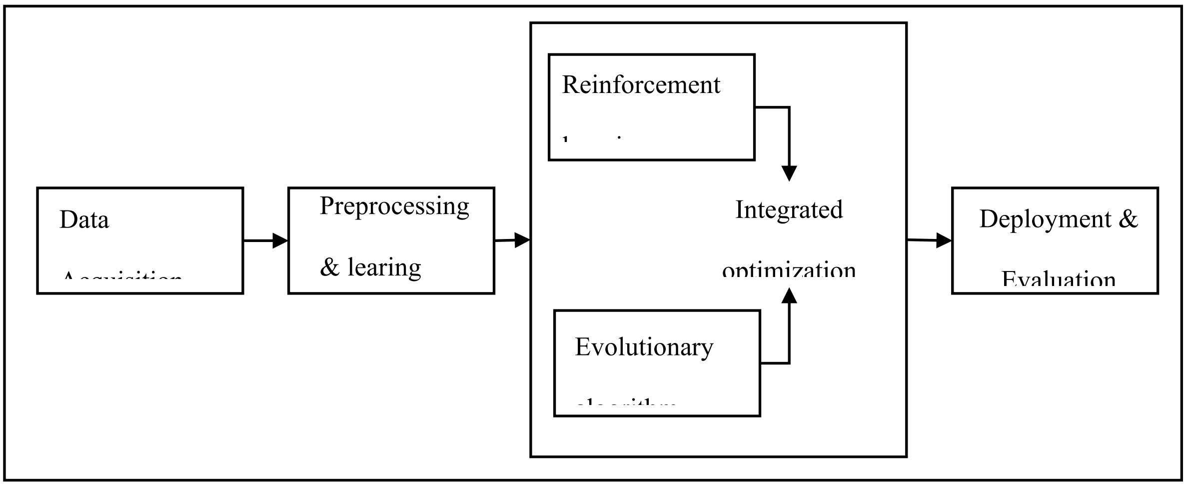

Figure 1: Architecture of the AI-Driven Dynamic Curriculum Design Framework

The five main stages of the system are Data Acquisition, Pre-processing, Learner Profiling, Hybrid RL-EA Engine and Learning Platform as shown in Figure 1. Should contain arrows between "Learner Interaction" and "RL-EA Optimization.

Dataset Collection and Educational Data Sources

The data collected from the experimental settings are from digital learning platforms, Learning Management System (LMS), and online educational repositories. Data includes learner demographics, quiz scores, assignment performance data, course completion data, logs of interactions, attendance data, engagement time data, and learning behavior measurements.

The data collected are segmented into structured attributes (academic performance indicators) and unstructured attributes (learner interaction patterns). The student learning progression and adaptability of curriculum are well represented in a framework using these educational datasets.

Some of the critical data collected for the key datasets include: Student ID, duration of learning, assessment result, engagement level, completion of topic, knowledge retention score, and curriculum progression level.

Data Preprocessing

If any data needs to be preprocessed, it can be preprocessed to improve the quality of the data set and make it simpler to train the model. Means and interpolation are used for values that are missing. Eliminates redundant data and inconsistent data for increased data reliability. Different educational attributes are feature normalized.

The normalization process is computed using Min-Max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

In equation (1), X represents the original feature value, X_{min} and X_{max} denote the minimum and maximum feature values, respectively.

Feature extraction is further conducted to identify significant learner attributes affecting curriculum adaptation and learning performance.

Learner Profiling Module

The learner profiling module classifies the students according to their academic capacity, learning speed, behavior in learning, and knowledge retention. The clustering algorithm is employed to put learners with the same educational characteristics in the same clusters. This module helps the curriculum adaptation engine with customization of the learning paths.

The learner performance score is calculated as:

$$LP = \frac{w_1A + w_2E + w_3R + w_4C}{w_1 + w_2 + w_3 + w_4} \quad (2)$$

The academic performance A, the level of engagement E, the retention score R, the course completion rate C, and the weighting coefficients $w_1, w_2, w_3,\ and\ w_4$ are given in equation (3). The learner profiles generated are saved for ongoing adaptive curriculum optimization.

Reinforcement Learning-Based Curriculum Adaptation

The Reinforcement Learning module acts as the intelligent decision-making engine of the proposed framework. The RL agent will continually engage with the learning environment and choose the optimal curriculum sequences from learner performance and feedback.

The learning environment consists of states, actions, rewards, and policy functions. The state depicts where the learner is in their education, their level of knowledge, whether they are engaged or not, and their stage of progress. Actions are related to the curriculum decisions made, such as the recommendation for topics, difficulty level, and the selection of learning paths. Rewards are assigned according to learner improvement and engagement enhancement.

The cumulative reward optimization function is defined as:

$$Q(s,a) = Q(s,a) + \alpha\left[r + \gamma \max Q\left(s', a'\right) - Q(s,a)\right] \quad (3)$$

In equation (3), $Q(s,a)$ denotes the quality value of state-action pairs, α represents the learning rate, r indicates the immediate reward, and γ is the discount factor.

The RL agent continually optimizes curriculum policies for long-term performance in the education domain and adaptive learning efficiency.

Evolutionary Algorithm Optimization

The RL framework is combined with Evolutionary Algorithms in order to improve the optimization process efficiency and prevent the possibility of local optimum stagnation. To evolve curriculum structures and optimize learning pathways, genetic algorithm (GA)-based optimization is used.

The evolutionary optimization process consists of the population initialization, fitness evaluation, selection, crossover, and mutation operations. Chromosomes code the sequences of curriculum, which consist of learning modules and arrangements of topics.

The fitness function is calculated using:

$$Fitness = \alpha P + \beta E + \gamma R \quad (4)$$

In equation (4), P denotes academic performance improvement, E represents engagement enhancement, and R indicates retention efficiency. The coefficients $\alpha, \beta, and\ \gamma$ control the contribution of each parameter.

The crossover operation creates new curriculum combinations, and the mutation process adds diversity in the optimization process. The optimized curriculum designs are subsequently passed to the RL adaptation engine for further optimization.

Hybrid RL-EA Integration Model

The hybrid model is a combination of the adaptive decision-making ability of Reinforcement Learning and the strength to perform global optimization of the Evolutionary Algorithms. RL module adjusts curriculum recommendations dynamically according to the interaction of learners, and EA module optimizes the structure of the curriculum for a better learning process and convergence.

The integrated objective function is expressed as:

$$O = \lambda_1 A + \lambda_2 E + \lambda_3 K - \lambda_4 C \quad (5)$$

In equation (5), A represents academic improvement, E denotes engagement level, K corresponds to knowledge retention, C indicates computational cost, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are optimization coefficients.

The hybrid integration guarantees an adaptive change of curriculum while minimizing computational complexity and increasing flexibility.

Algorithm 1: Hybrid Reinforcement Learning and Evolutionary Algorithm for Dynamic Curriculum Optimization

Input:

- Educational dataset D
- Learner interaction records
- Academic performance metrics
- Engagement and retention scores

Output:

- Optimized personalized curriculum pathway
- Adaptive learning recommendations

Step 1: Data Acquisition

1. Collect educational data from LMS, online platforms, and repositories.
2. Extract learner attributes:
    - Quiz scores
    - Assignment performance
    - Engagement duration
    - Completion rate
    - Knowledge retention

Step 2: Data Preprocessing

3. Remove duplicate and inconsistent records.
4. Handle missing values using mean imputation.
5. Normalize dataset using Min-Max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

6. Perform feature extraction for significant learner attributes.

Step 3: Learner Profiling

7. Cluster learners based on:
    - Academic ability
    - Learning speed
    - Engagement behavior
    - Retention capacity
8. Compute learner performance score:

$$LP = \frac{w_1 A + w_2 E + w_3 R + w_4 C}{w_1 + w_2 + w_3 + w_4}$$

9. Store learner profiles for adaptive curriculum generation.

Step 4: Reinforcement Learning Curriculum Adaptation

10. Initialize RL environment with:

- States S
- Actions A
- Rewards R

11. Select curriculum actions based on learner state.
12. Compute reward according to learner improvement and engagement.
13. Update Q-values using:

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma \max\ Q(s^{'},a^{'}) - Q(s,a)]$$

14. Continuously optimize curriculum policy.

Step 5: Evolutionary Algorithm Optimization

15. Initialize curriculum population as chromosomes.
16. Evaluate fitness of each curriculum structure using:

$$Fitness = \alpha P + \beta E + \gamma R$$

17. Apply:
- Selection
- Crossover
- Mutation
18. Generate optimized curriculum combinations.

Step 6: Hybrid RL-EA Integration

19. Integrate optimized EA curriculum with RL adaptation engine.
20. Compute integrated optimization objective:

$$O = \lambda_1 A + \lambda_2 E + \lambda_3 K - \lambda_4 C$$

21. Update adaptive learning pathways dynamically.

Step 7: Deployment and Evaluation

22. Deploy an optimized curriculum within an intelligent learning platform.
23. Monitor learner interactions in real time.
24. Evaluate system performance using:
- Curriculum adaptation accuracy
- Learning efficiency
- Engagement rate
- Knowledge retention
- Computational cost
25. Output optimized personalized curriculum recommendations.

In the area of personalized education, Algorithm 1 is a hybrid of Reinforcement Learning (RL) and Evolutionary Algorithms (EA) that aims to develop an adaptive curriculum optimization system. RL module dynamically updates learning pathways according to interactions and performance feedback of learners, and EA module optimizes curriculum structures via genetic operations, including selection, crossover, and mutation. In the smart learning environment, the hybrid mechanism is constantly optimized to enhance the engagement of learners, their academic achievement, knowledge retention, and the adaptability of learning courses.

System Architecture and Implementation

The proposed framework is applied with the help of AI-based and machine learning libraries written in Python. Data preprocessing and analysis are done using NumPy and Pandas. Reinforcement Learning algorithms are designed with the frameworks of TensorFlow and PyTorch. The evolutionary optimization operations are created using the evolutionary computation library called DEAP.

The educational data management system uses MySQL databases, and the web-based learning interface is created using Flask and ReactJS technologies. In real-time, the interaction between the learners is monitored with the help of cloud-based educational servers that are connected to RESTful APIs.

The system is executed on a high-performance computing environment with Intel Core i9 processors, NVIDIA RTX GPU acceleration, 32 GB RAM, and Ubuntu-based operating systems to support large-scale curriculum optimization.

Performance Evaluation Metrics

To evaluate the proposed AI-powered adaptive learning framework, several educational and computational metrics were used to assess its effectiveness in adaptive learning environments. The hybrid Reinforcement Learning and Evolutionary Algorithm model has been tested for the Accuracy of curriculum adaptation, engagement rate of learners, academic improvement, efficient knowledge retention, convergence speed, and reward optimization performance. The experimental results showed that the new system was more accurate in personalization and had better interaction with the learner than the traditional curriculum recommendation system. The model also demonstrated the ability to converge rapidly, to optimize curriculum, and to lower the computational complexity and increase the efficiency of making adaptive decisions in the dynamically changing educational context.

Experimental Workflow

The experimental workflow starts with the collection of the educational data, then the data is preprocessed, and ultimately, a learner is profiled. The processed data is then fed to the Reinforcement Learning module for generating the adaptive curriculum. Optimization of the structures of the curriculum, based on evolutionary optimization, further optimizes the efficiency of learning and stability of convergence.

The optimized learning pathways are implemented on the intelligent learning platform, and the platform constantly adjusts the adaptive curriculum model according to learners' interaction. The concluding assessment benchmarks the proposed hybrid system with conventional AI-driven curriculum systems, yielding further insights into the improvements in personalization, engagement, adaptability, and learning outcomes.

4. Results

Overall Performance Analysis

The proposed AI-Driven Dynamic Curriculum Design framework based on Reinforcement Learning (RL) and Evolutionary Algorithms (EA) showed significant improvements in terms of both adaptive learning and the efficiency of curriculum optimization, and in terms of engaging learners, over traditional curriculum recommendation systems. The learning data were collected from intelligent learning platforms that recorded the interactions between the learner and the platform, learning performance, and engagement indicators, and the uses were explored through experimental assessments.

The hybrid RL-EA framework had a higher accuracy in curriculum adaptation than the other three frameworks since it could continuously adapt the learning pathway according to the learner's behavior and learning progress. The integration of evolutionary optimization improved convergence stability and reduced the limitations commonly associated with standalone reinforcement learning approaches.

The overall prediction accuracy was computed using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

The engagement improvement rate was evaluated using:

$$Engagement\ Rate = \frac{Active\ Learners}{Total\ Learners} \times 100 \tag{7}$$

The reward optimization efficiency was calculated as:

$$Reward\ Efficiency \frac{=\ Total\ Reward}{Training\ Episodes} \tag{8}$$

In equations (6) - (8), Accuracy represents the overall correctness of educational predictions, Precision is the percentage of correct education predictions for positive outcomes, and Recall is the percentage of actual positive education outcomes correctly identified by the model, with TP and TN representing true positive and true negative, and FP and FN representing false positive and false negative, respectively.

Curriculum Adaptation Performance

The curriculum adaptation analysis demonstrated that the proposed hybrid framework effectively personalized learning pathways according to learner capabilities and engagement behavior. The system continuously optimized curriculum sequences with reinforcement learning policies and evolutionary optimization improved the efficiency of curriculum diversity and adaptation.

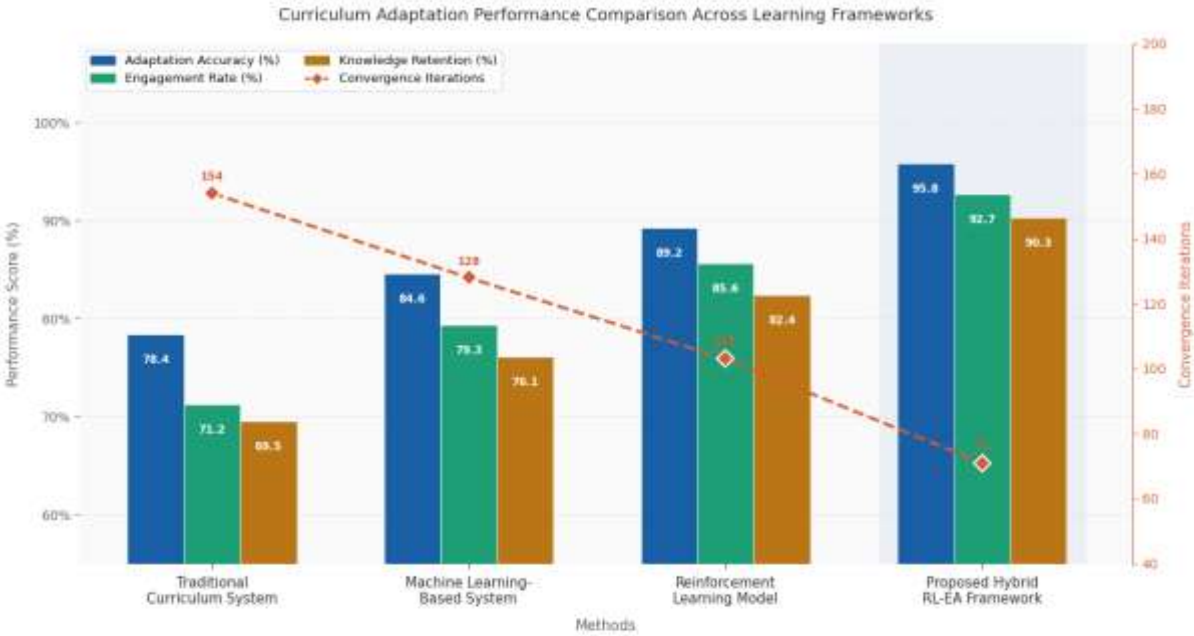

Figure 2: Curriculum Adaptation Performance Comparison

The effectiveness of the different learning frameworks in terms of the Accuracy of curriculum adaptation, engagement rate, and knowledge retention is compared in Figure 2, which demonstrates the high level of effectiveness and rapid convergence of the proposed hybrid RL-EA framework.

Academic Performance Improvement

The hybrid framework significantly enhanced the academic performance of learners by offering dynamic curriculum complexity and providing an appropriate learning module recommendation based on the learner's progress.

The academic improvement metric was calculated using:

$$Academic\ Improvement = \frac{Final\ Score - Initial\ Score}{Initial\ Score} \times 100 \qquad (9)$$

In equation (9), the $Academic\ Improvement$ percentage measures the relative increase in a student's performance by comparing the difference between the $Final\ Score$ and the $Initial\ Score$ with respect to the initial score.

The Academic Improvement percentage in equation (9) is a measure of the relative improvement that a student has achieved: what is the difference between the Final Score and the Initial Score compared to the Initial Score.

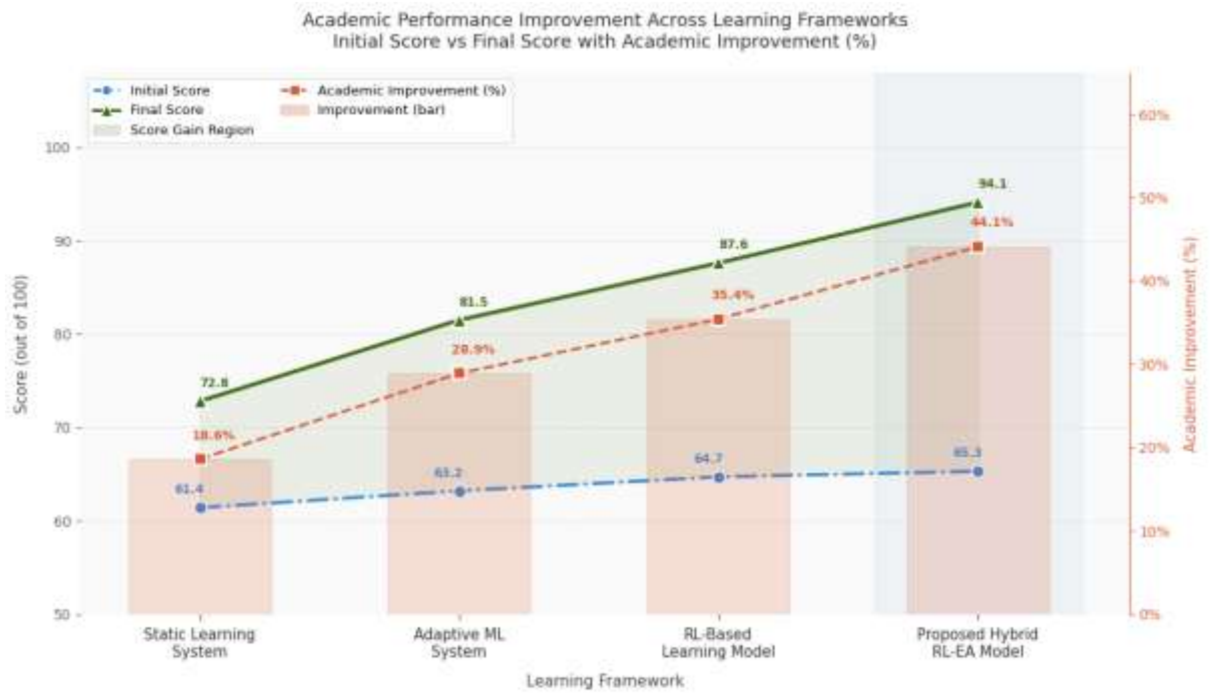

Figure 3: Academic Performance Improvement Analysis

The adaptive curriculum optimization concept can be clearly seen through a comparison of learners' initial scores, final scores, and the percentage of academic improvement in each learning system, as shown in Figure 3.

Reward Optimization and Learning Efficiency

By implementing the reinforcement learning reward mechanism, the proposed system was able to improve educational outcomes through successive training episodes. The evolutionary optimization added to the integration enhanced exploration and prevented getting stuck at local optima.

Figure 4: Performance Comparison of AI-Based Curriculum Optimization Models Using Reward and Learning Efficiency Metrics. A): Average Reward Optimization Trend Across AI Models. B): Learning Efficiency Trend Across AI Models.

Figure 4 A) shows the average reward of various Curriculum optimization models based on AI. The standalone RL, GA, and Deep Learning models achieve reward scores of 1016, 658, and 689, respectively, which are lower than the proposed Hybrid RL-EA model's reward score of 928. The visualization also shows the differences in computational costs between models.

The comparison of the learning efficiency of the different AI-based curriculum optimization methods is shown in Figure 4 B). The proposed Hybrid RL-EA Framework can achieve the highest learning efficiency of 94.8%, which proves that the personalized learning adaptation and curriculum recommendation performance of the model is improved, and the computing cost is moderate compared with other models.

Learner Engagement and Retention Analysis

The proposed framework has shown great potential to enhance learners' engagement and learning retention by adapting the curriculum sequence and learning interaction to each learner. The system was able to adapt its educational content on the fly, thanks to real-time monitoring of the learners.

The retention efficiency was measured using:

$$Retention\ Efficiency = \frac{Retained\ Knowledge}{Total\ Learned\ Knowledge} \times 100 \qquad (10)$$

In equation (10), the $Retention\ Efficiency$ percentage evaluates how effectively learners retain acquired knowledge by comparing the $Retained\ Knowledge$ to the $Total\ Learned\ Knowledge$.

Table 1: Learner Engagement and Retention Performance

System	Engagement Rate (%)	Retention Efficiency (%)	Course Completion Rate (%)
Conventional E-Learning	70.8	68.4	72.1
Adaptive ML Platform	80.5	77.6	81.3
RL-Based Adaptive System	87.9	84.1	88.6
Proposed Hybrid RL-EA Framework	93.4	91.7	95.2

Table 1 shows a learner engagement and retention performance comparison of four curriculum systems. Retention efficiency is 68.4% for the Conventional E-Learning system, and for the Adaptive ML Platform and RL-Based Adaptive System, there are progressive improvements. The proposed Hybrid RL-EA Framework is the most effective with regard to engagement rate (93.4%), retention efficiency (91.7%), and course completion rate (95.2%).

5. Ablation Study

Impact of Reinforcement Learning and Evolutionary Components

The ablation study was performed to determine the contribution of each component in the proposed hybrid system. Various configurations were tried, with the removal of certain modules like Reinforcement Learning, Evolutionary Optimization, and Learner Profiling.

Table 2: Ablation Study of the Proposed Framework

Framework Configuration	Accuracy (%)	Engagement Rate (%)	Academic Improvement (%)	Convergence Iterations
Full Proposed RL-EA Framework	95.8	92.7	44.1	71
Without the Evolutionary Algorithm	90.6	86.2	36.4	101
Without Reinforcement Learning	87.3	82.7	31.5	118
Without the Learner Profiling Module	84.5	79.4	27.8	126
Without Reward Optimization	82.1	76.3	24.6	137

Table 2 showed that the performance of convergence and optimization efficiency was significantly decreased without the Evolutionary Algorithm. Likewise, the curriculum adaptability and performance of the learner were impaired when Reinforcement Learning was removed. The learner profiling module also played a significant role in personalization accuracy and academic improvement.

Comparative Analysis

Table 3: Comparative Performance Analysis of the Proposed Hybrid RL-EA Framework Against State-of-the-Art Adaptive Curriculum Optimization Methods

Article in reference	Method / System	Adaptation Accuracy (%)	Engagement Rate (%)	Retention Efficiency (%)	Course Completion Rate (%)	Academic Improvement (%)	Learning Efficiency (%)
[22]	RL-Based Adaptive Curriculum Generation	87.3	87.9	84.1	88.6	36.4	87.6
[23]	Deep Learning-Based Adaptive System (Bi-LSTM)	88.6	83.2	81.5	84.7	33.5	88.3
Proposed	**Hybrid RL-EA Framework**	**95.8**	**93.4**	**91.7**	**95.2**	**44.1**	**94.8**

Table 3 presents the proposed Hybrid RL-EA Framework and two published baseline methods in terms of six performance metrics. The proposed framework consistently outperforms the RL-Based Adaptive Curriculum Generation [22] and Deep Learning-Based Adaptive System [23] in all metrics, with the highest adaptation accuracy of 95.8%, engagement rate of 93.4%, and learning efficiency of 94.8%, which shows that the proposed framework is effective in personalized curriculum optimization.

6. Discussion

The proposed Hybrid RL-EA Framework demonstrated outstanding performance across all evaluation metrics. It achieved a curriculum adaptation accuracy of 95.8%, engagement rate of 93.4%, retention efficiency of 91.7%, course completion rate of 95.2%, academic improvement of 44.1%, and learning efficiency of 94.8%, consistently outperforming conventional e-learning, adaptive ML platforms, RL-based systems, and deep learning baselines. The ablation study also demonstrated that each component: reinforcement learning, evolutionary optimization, and learner profiling, were all playing a critical role in the overall performance. The more successful results demonstrate that when paired with EA's ability to perform global optimization, there is a tremendous synergy between RL's dynamic decision making which can help with personalized curriculum design. Overall, the RL module manages to adapt the learning pathways on the fly as a function of learner activity, while the EA algorithm avoids the local optimum traps and reduces the number of iterations to 71, which is much less than the standalone cases. The learner profiling module also helps to achieve personalisation by successfully segmenting students based on their academic ability, engagement and retention capabilities. The findings suggest that hybrid AI-based solutions can be a game-changer in intelligent learning environments, providing a highly personalized, adaptive, and efficient learning experience. This can be considered as a scalable solution that helps to drive engagement, retention, and academic Success, making it an effective solution for next-gen LMS and online learning platforms looking for ways to improve learning outcomes. The framework showed promise, but was only explored with one education dataset from one digital learning platform, meaning there is the potential it may not be generalizable to other disciplines of study and to other learners. In addition, the practical aspects, such as data privacy, scalability of systems, and computational infrastructures were not adequately considered. It should be evaluated in other education data sets, across subject areas, age groups and learning environments in order to validate the framework. Implementing explainable AI mechanisms can improve the explainability of curricular recommendations. The study of federated learning approaches is able to address data privacy concerns and enable adaptive personalization, among other things, if further research work is done.

7. Conclusion

The traditional curriculum design systems do not meet individual student needs (various and dynamic) well, which causes poor engagement, low retention, and suboptimal academic outcomes. Standalone reinforcement learning is currently suffering from the problem of falling in the local optimum, and convergence speed is also too slow, and they lack personalization capabilities. In this paper, these problems were addressed by suggesting an AI-based Dynamic Curriculum Design Framework, which combines Reinforcement Learning and Evolutionary Algorithms to provide adaptive, personalized, and optimized educational pathways. The proposed Hybrid RL-EA Framework has been extensively tested under various performance metrics and yielded the best results. The framework successfully adapted the curriculum with 95.8%, engaged with the students 93.4%, retained them with 91.7%, and achieved a completion rate of 95.2% compared to all baseline systems, such as conventional e-learning (70.8%), adaptive ML platforms (80.5%), and standalone RL-based systems (87.9%). The results were better, with academic improvement of 44.1%, a learning efficiency of 94.8%, and convergence achieved in only 71 iterations for the full configuration, down from 137 iterations for reduced configurations. The ablation study demonstrated that the overall performance of the system was clearly impaired by the deletion of any of the three main types of component reinforcement learning, evolutionary optimization, or learner profiling. The framework proposed here states that it is possible to measure the superior personalization, engagement, and academic outcomes achieved when implementing AI in a hybrid way, that is, combining reinforcement learning and evolutionary optimization. The learner profiling module is a fundamental part of teaching for targeted curriculum adaptation. This framework provides a scalable and efficient foundation for developing next-generation intelligent educational platforms capable of transforming personalized learning experiences across diverse academic environments.

8. Author contribution

Conflict of interest

The authors declare no conflict of interest.

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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