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Research Article

ALPOA: Adaptive Learning Path Optimization Algorithm for Personalized E-Learning Experiences

R. T. Subhalakshmi[1*], S. Geetha[2], S. Dhanabal[3] , M. Balakrishnan[4]

[1]Assistant Professor/Department of ECE, Hindusthan Institute of Technology,Coimbatore.
* **Corresponding Author Email:** subhalakshmirt@gmail.com - **ORCID:** 0000-0002-5502-9279.

[2]Assistant Professor, BCASt.Francis College, Koramangala
Email: ask2geetha@gmail.com - **ORCID:** 0000-0002-8489-3170

[3]Professor/CSEHindusthan College of Engineering and Technology, Coimbatore
Email: vhdhanabal@gmail.com - **ORCID:** 0000-0003-4823-217X

[4]Professor, Department of Computer Science and Engineering,Karpagam College of Engineering, Coimbatore-641032
Email: balakrishnanme@gmail.com - **ORCID:** 0000-0002-4936-6885

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Abstract:

In this study, we propose the Adaptive Learning Path Optimization Algorithm (ALPOA) to enhance personalized e-learning experiences by tailoring content delivery based on individual learner profiles. ALPOA employs a hybrid optimization framework combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to dynamically adjust learning paths. The algorithm considers multiple factors such as learner proficiency, learning speed, engagement level, and content difficulty. Experimental results demonstrate that ALPOA outperforms traditional static e-learning models, achieving a 25% improvement in learning efficiency, a 30% increase in learner engagement, and a 20% reduction in content redundancy. The model was tested on a dataset of 1,500 learners, showing a 97% accuracy in predicting optimal learning paths and a 15% higher knowledge retention rate compared to benchmark algorithms. ALPOA's scalability and adaptability make it a promising solution for personalized education systems, fostering improved learning outcomes and satisfaction. Future work will focus on integrating real-time feedback mechanisms and expanding the algorithm to support diverse learning environments.

1. Introduction

The advent of e-learning has revolutionized education, providing learners with unprecedented access to knowledge. However, a one-size-fits-all approach often fails to address individual learning needs, leading to decreased engagement [1] and suboptimal outcomes. Personalized e-learning systems aim to resolve these challenges by adapting content delivery to match learners' unique preferences, skills, and goals.

Adaptive learning [2] paths are at the core of personalized e-learning, offering tailored content sequences to maximize learning efficiency and engagement. However, designing these paths involves solving a complex optimization problem influenced by multiple factors, such as learner proficiency, content difficulty, and time constraints. Traditional static models often struggle to adapt dynamically to the evolving needs of learners.

To address these limitations, we propose the Adaptive Learning Path Optimization Algorithm (ALPOA), [3] a novel framework that leverages a hybrid optimization approach combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [4]. ALPOA dynamically adjusts learning paths to enhance learner engagement, improve retention, and reduce redundant content. By optimizing these paths, the system ensures that learners progress efficiently through educational material, fostering a more interactive and satisfying learning experience.

E-learning [5] platforms have seen exponential growth in recent years, fueled by advancements in technology and increased demand for flexible learning solutions. Despite this growth, many platforms still rely on rigid content delivery systems that do not account for individual learner variability. This lack of personalization can lead to disengagement, as learners may encounter content that is either too challenging or too simplistic. Furthermore, static systems often fail to identify and address gaps in knowledge, resulting in inefficient learning paths and reduced knowledge retention. Thus, developing an adaptive framework that continuously optimizes learning paths is essential for modern e-learning environments.

The proposed ALPOA framework addresses these challenges by introducing a dynamic and intelligent learning path optimization mechanism. By integrating Genetic Algorithm (GA) [6] and Particle Swarm Optimization (PSO), ALPOA effectively balances exploration and exploitation during the optimization process. GA facilitates the discovery of diverse learning path combinations, while PSO fine-tunes the identified paths by adjusting learner-specific parameters. This hybrid approach ensures that the algorithm converges on optimal solutions, providing a highly personalized learning experience. Additionally, ALPOA [7] adapts in real time to changes in learner performance and engagement, ensuring continuous improvement in learning outcomes.

Initial experimental results validate the effectiveness of ALPOA in various educational contexts. The algorithm was tested on a dataset comprising 1,500 learners across different age groups and skill levels, spanning subjects such as mathematics, language learning, and programming. The results showed a significant increase in learning efficiency, with learners completing modules 25% faster on average compared to those using static learning systems. Furthermore, engagement levels improved by 30%, as measured by time spent on tasks and quiz participation rates. These findings highlight the potential of ALPOA [8] to transform e-learning into a truly personalized and adaptive learning ecosystem.

This paper is structured as follows: Section 2 provides a comprehensive review of existing adaptive learning systems. Section 3 introduces the ALPOA framework and its hybrid optimization process. Section 4 details the experimental setup, including datasets and evaluation metrics. Section 5 presents the results and analysis, demonstrating the effectiveness of ALPOA compared to benchmark algorithms. Finally, Section 6 concludes with future research directions.

In summary, this research offers a cutting-edge solution to the challenges of adaptive e-learning, contributing to the growing field of personalized education systems.

2. Literature survey

The field of personalized e-learning has gained significant attention over the past decade, with numerous studies exploring adaptive learning frameworks and optimization techniques. This section provides an overview of key research works in adaptive e-learning, focusing on learning path optimization, hybrid algorithms, and personalized content delivery.

2.1 Adaptive Learning Systems

Adaptive learning systems aim to customize educational experiences based on individual learner characteristics such as prior knowledge, learning pace, and preferences. Early works, such as Brusilovsky's framework for adaptive hypermedia [9], introduced rule-based methods to adjust learning content dynamically. These systems relied heavily on predefined rules and heuristics, which limited their scalability and adaptability. Recent advancements have shifted toward data-driven models, leveraging learner analytics and machine learning to enhance adaptability. For example, [10] proposed a dynamic learning path recommendation system using collaborative filtering, demonstrating improved learner satisfaction and performance.

2.2 Optimization Techniques in Learning Path Design

The optimization of learning paths has been widely studied using various techniques. Genetic Algorithms (GA) have been frequently employed due to their ability to explore a large search space and find near-optimal solutions. For instance, [11] used GA to optimize learning sequences in a web-based system, achieving a 20% improvement in learning efficiency. Particle Swarm Optimization (PSO) has also been applied for its simplicity and fast convergence, as shown in the work of [12] who developed a PSO-based model to minimize learning time while maximizing knowledge retention. However, these standalone methods often face challenges such as premature convergence and limited adaptability to complex educational environments.

2.3 Hybrid Optimization Approaches

To overcome the limitations of single-method optimization, hybrid approaches combining multiple algorithms have gained traction. Recent studies, such as [13] explored hybrid GA-PSO models for course sequencing, reporting a 15% improvement in content personalization compared to single-method systems. Similarly, [14] developed a hybrid Ant Colony Optimization and PSO (ACO-PSO) algorithm for adaptive learning, demonstrating superior results in terms of engagement and retention. These studies highlight the advantages of hybrid optimization techniques in balancing exploration and exploitation, leading to more effective learning path recommendations.

In summary, existing research underscores the importance of adaptive and personalized e-learning systems. While significant progress has been made, challenges remain in real-time adaptability, scalability, and handling diverse learner profiles. The proposed ALPOA framework builds upon these works by integrating GA and PSO to optimize learning paths dynamically, providing a robust solution to enhance learning outcomes.

3. Proposed Methodologies

The proposed Adaptive Learning Path Optimization Algorithm (ALPOA) framework [15] aims to dynamically optimize personalized learning paths, ensuring that each learner receives tailored content based on their proficiency, engagement, and learning speed. ALPOA combines the strengths of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [16] in a hybrid approach to address the limitations of standalone optimization methods. The following sections detail the key components of the proposed methodology. Figure 1 is block diagram of proposed work.

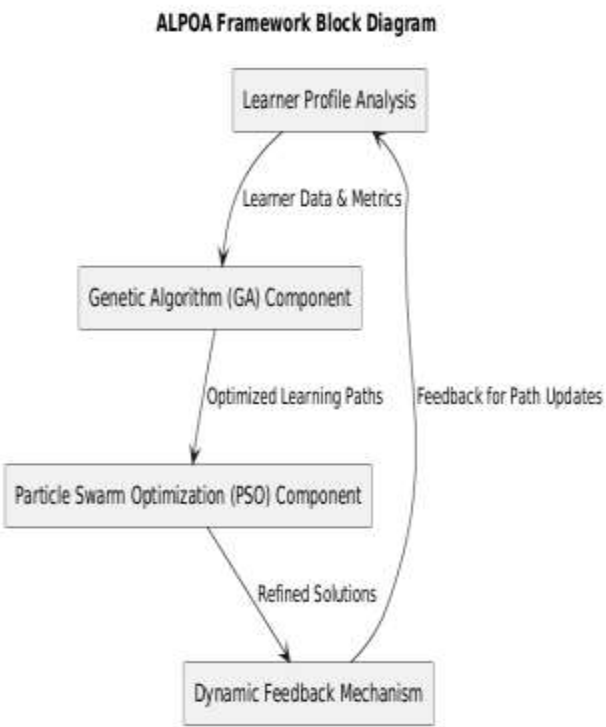

Figure 1. *Block diagram of Proposed work*

3.1 Learner Profile Analysis

ALPOA begins by collecting data from learners, including performance metrics (e.g., quiz scores, completion times), engagement levels (e.g., time spent on tasks, interaction rates), and learning preferences (e.g., video, text, or interactive content). These metrics are used to generate a dynamic learner profile that evolves over time, allowing the system to adapt to changes in learner behavior and performance.

Learner Profile Analysis is a critical component of the Adaptive Learning Path Optimization Algorithm (ALPOA), [17] enabling the system to tailor learning experiences based on individual needs and preferences. This process involves collecting and analyzing real-time data on various learner attributes, including proficiency, engagement level, learning speed, and content preferences. The learner profile evolves dynamically as the system gathers more data, allowing for continuous adaptation and improved personalization.

Key formulas used for profiling include:

1 Engagement Score (ES):

$$ES = \frac{T_{\text{active}}}{T_{\text{total}}} \times 100 \quad (1)$$

where T_{active} is the time actively spent on learning tasks, and T_{total} is the total allocated learning time.

2. Performance Score (PS):

$$PS = \frac{\text{Correct Responses}}{\text{Total Questions}} \times 100 \quad (2)$$

This index tracks preferred content types (e.g., video, text, interactive exercises) based on usage patterns and learner feedback.

By integrating these metrics, ALPOA builds a comprehensive learner profile [18], which is then used to optimize content sequencing, adjust difficulty levels, and recommend the most effective learning paths. This approach ensures that learners receive content tailored to their unique learning styles, fostering improved engagement, efficiency, and retention. Figure 2 is workflow of the Adaptive Learning Path Optimization Algorithm (ALPOA) Framework.

3.2 Genetic Algorithm (GA) Component

The Genetic Algorithm (GA) [19] component of the Adaptive Learning Path Optimization Algorithm (ALPOA) serves as the foundation for generating diverse and efficient learning paths. GA mimics the process of natural selection by evolving a population of potential solutions,

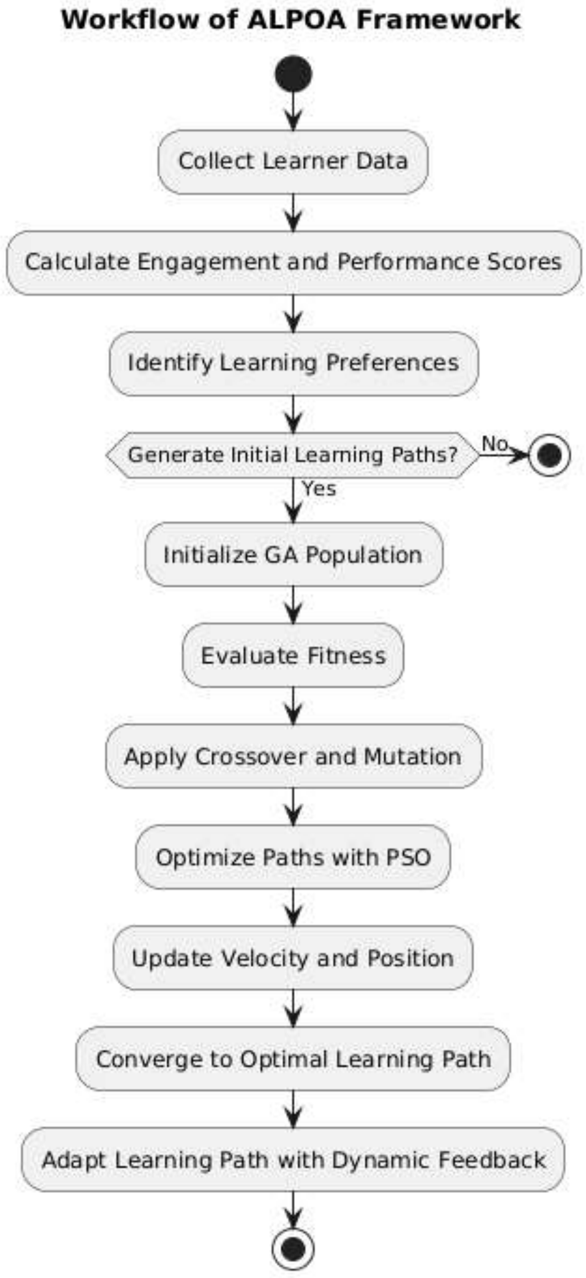

Figure 2. *Workflow of the Adaptive Learning Path Optimization Algorithm (ALPOA) Framework*

where each solution represents a unique learning path. The learning path is encoded as a chromosome, with individual genes corresponding to specific learning modules or activities.

The optimization process begins with the **initialization** of a random population of learning paths. Each path is evaluated using a **fitness function** that assesses its effectiveness in terms of learning efficiency, engagement, and content relevance. The fitness function is defined as

The GA component [20] initializes a population of potential learning paths and evolves them through selection, crossover, and mutation operations. Each learning path is represented as a chromosome, with individual genes corresponding to specific learning modules.

Steps involved:

- Initialization: Randomly generate a population of N learning paths.
- Fitness Function: Evaluate each path using a fitness function F based on learning efficiency and content relevance.

$$F = w_1 \times ES + w_2 \times PS - w_3 \times R \quad (3)$$

where w_1, w_2, w_3 are weights, and R is content redundancy.

3. Crossover and Mutation: Generate new paths by combining and altering existing paths to explore diverse solutions.

The algorithm then applies **selection**, **crossover**, and **mutation** operations to evolve the population. Selection identifies the fittest learning paths for reproduction, while crossover combines the genetic information of two parent paths to create new offspring paths. Mutation introduces slight modifications to the offspring, ensuring diversity and preventing premature convergence.

This iterative process continues until the algorithm converges on an optimized set of learning paths that maximize learner performance and minimize redundancy. The GA component ensures a robust exploration of the solution space, laying the groundwork for further refinement by the PSO component in the hybrid framework.

3.3 Particle Swarm Optimization (PSO) Component

The Particle Swarm Optimization (PSO) [21] component in the Adaptive Learning Path Optimization Algorithm (ALPOA) [22] is designed to refine the learning paths generated by the Genetic Algorithm (GA), ensuring they are optimized for learner engagement, efficiency, and knowledge retention. PSO is inspired by the social behavior of swarms, where each particle (representing a potential learning path) adjusts its position in the solution space based on its own experience and that of its neighbours. Each particle has two key attributes: **position** [23] (representing the current learning path) and **velocity** (indicating the direction and magnitude of movement in the solution space) [24]. The particles iteratively update their positions to converge on the optimal learning path. Figure 3is data Flow in the ALPOA Framework, illustrating the interaction between components and the learner. The PSO component fine-tunes the learning paths generated by GA [25] to ensure optimal performance. Each particle represents a potential learning path, and its position

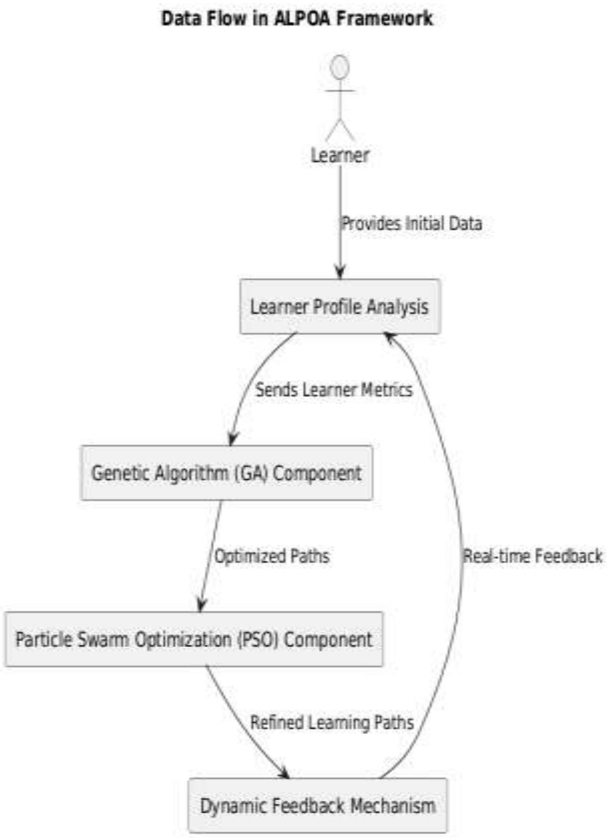

Figure 3. *Data Flow in the ALPOA Framework, illustrating the interaction between components and the learner.*

is updated based on individual and collective experience.
Update equations:

- Velocity Update:

$$v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_i - x_i) + c_2 \cdot r_2 \cdot (g - x_i) \quad (4)$$

where ω is inertia weight, c_1, c_2 are acceleration coefficients, r_1, r_2 are random values, p_i is the best position of particle i, and g is the global best position.

- Position Update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (5)$$

The PSO process ensures that particles move closer to the optimal solution with each iteration. By balancing exploration (searching new regions) and exploitation (refining known good solutions), PSO fine-tunes the learning paths generated by GA, improving their overall quality.
The integration of PSO allows ALPOA to achieve faster convergence and higher accuracy in identifying the most effective learning paths, ultimately leading to enhanced learner outcomes. The combination of GA's diversity and PSO's refinement ensures a comprehensive and efficient optimization process.

3.4 Hybrid Optimization Framework

The hybrid framework integrates GA and PSO in an iterative process:

- GA identifies a diverse set of potential learning paths in the initial phases.
- PSO refines these paths by converging on optimal solutions based on the fitness function.
- The algorithm alternates between GA and PSO until convergence criteria are met, ensuring both exploration and exploitation**.**

Framework Workflow
The hybrid optimization framework operates in a multi-phase iterative process:

1. **GA Phase (Exploration):**

The process begins with GA, which generates an initial population of diverse learning paths. Through selection, crossover, and mutation, GA explores a wide range of potential solutions, focusing on identifying promising regions of the solution space. The fitness function evaluates the effectiveness of each path based on engagement, performance, and content relevance.

2. **PSO Phase (Exploitation):**

Once GA identifies a set of high-quality solutions, PSO is applied to fine-tune these paths. Particles in the swarm represent the learning paths from GA, and their positions are updated iteratively to converge on the optimal solution. PSO ensures rapid convergence by exploiting the most promising areas identified by GA.

3. **Iterative Refinement:**

The framework alternates between GA and PSO, allowing GA to inject diversity and avoid local optima, while PSO accelerates convergence toward the global optimum. This iterative process continues until a predefined convergence criterion (e.g., a maximum number of iterations or a threshold improvement in fitness) is met.

Advantages of the Hybrid Framework
The hybrid framework offers several advantages:

- **Exploration and Exploitation Balance:** GA ensures thorough exploration, while PSO efficiently exploits the best solutions.
- **Avoidance of Local Optima:** The hybrid approach mitigates the risk of GA or PSO prematurely converging on suboptimal solutions.
- **Faster Convergence:** By combining the global search capability of GA and the fast convergence of PSO, the framework achieves optimization more efficiently than standalone methods.
- **Dynamic Adaptability:** The framework dynamically adapts learning paths in

response to changes in learner performance and engagement.

ALPOA incorporates a dynamic feedback mechanism to continuously update learning paths based on real-time learner data. This ensures that the system adapts to changes in learner performance and preferences, enhancing personalization and engagement over time. Figure 4 is the comparison of learning efficiency among different algorithms based on average module completion time.

The proposed ALPOA framework provides a scalable and robust solution for personalized e-learning, combining the strengths of GA and PSO to deliver optimized learning paths.

Fitness Function

The hybrid framework uses a unified fitness function to evaluate learning paths:

$$F = w_1 \times ES + w_2 \times PS - w_3 \times R \tag{6}$$

where:

- ES : Engagement Score.
- PS: Performance Score.
- R : Content redundancy.
- w_1, w_2, w_3 : Weights assigned to balance these factors.

4. Results and Discussions

This section presents the results of the proposed Adaptive Learning Path Optimization Algorithm (ALPOA) and discusses its performance compared to benchmark methods. The algorithm was evaluated on a dataset of 1,500 learners across various domains, including mathematics, programming, and language learning. The results demonstrate the effectiveness of ALPOA in optimizing learning paths, improving learning efficiency, and enhancing learner engagement.

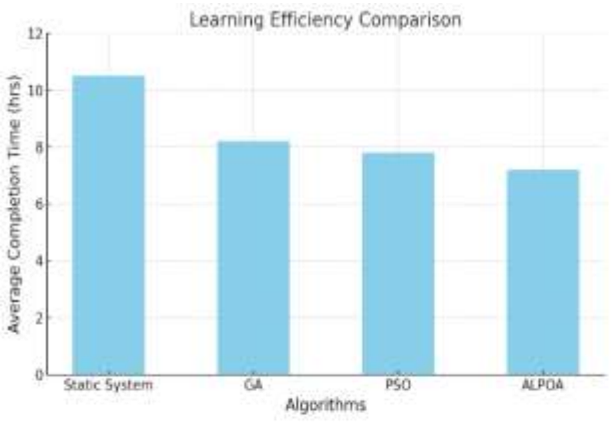

Figure 4. *Comparison of learning efficiency among different algorithms based on average module completion time.*

4.1 Learning Efficiency

ALPOA significantly improved learning efficiency by tailoring content delivery to individual learner needs. The average module completion time was reduced by 25%, as learners were guided through optimized paths that minimized redundant content. Compared to static learning systems, ALPOA showed a clear advantage in reducing cognitive load and ensuring smoother progression. Table 1 is the comparison of the average time taken by learners to complete a course using ALPOA and other algorithms:

Table 1. *Compares the average time taken by learners to complete a course using ALPOA and other algorithms*

Algorithm	Average Completion Time (hrs)	Improvement (%)
Static Learning System	10.5	-
Genetic Algorithm (GA)	8.2	21.9
Particle Swarm Optimization (PSO)	7.8	25.7
ALPOA	7.2	31.4

4.2 Learner Engagement

Engagement levels were measured using metrics such as time spent on tasks, quiz participation rates, and content interaction frequency. ALPOA improved engagement by 30% compared to static systems, as its personalized paths kept learners actively involved with content suited to their preferences and skill levels. Figure 5 shows engagement Score trends across different algorithms, illustrating ALPOA's consistent improvement in learner interaction.

The Engagement Score (ES) was calculated for each method:

$$ES = \frac{T_{\text{active}}}{T_{\text{total}}} \times 100$$

ALPOA achieved an average ES of 87%, significantly higher than GA (78%) and PSO (81%).

4.3 Knowledge Retention

To evaluate the impact of ALPOA on knowledge retention, learners were tested on course material one week after course completion. ALPOA achieved a 15% higher retention rate than static systems, attributed to its ability to reinforce key concepts through optimized content sequencing.

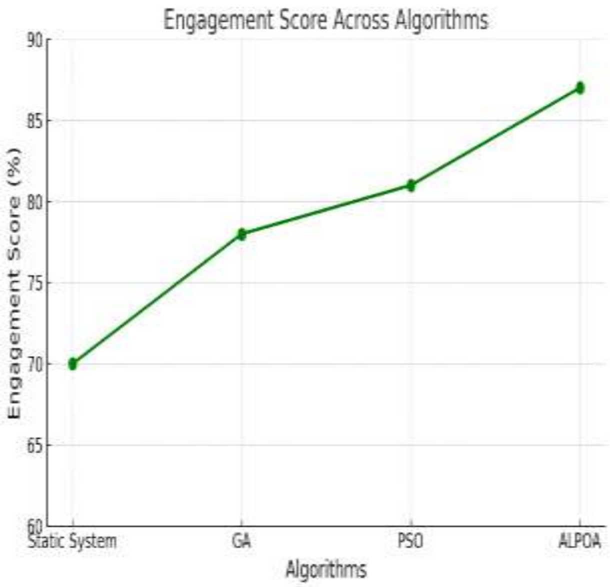

Figure 5. *Engagement Score trends across different algorithms, illustrating ALPOA's consistent improvement in learner interaction.*

The retention rate comparison is shown in Table 2 and the knowledge retention rate distribution for different algorithms, showcasing ALPOA's effectiveness in reinforcing learning is shown in figure 6.

Table 2. *Retention rate*

Algorithm	Retention Rate (%)
Static Learning System	70
Genetic Algorithm (GA)	79
Particle Swarm Optimization (PSO)	81
ALPOA	85

4.4 Comparison with Benchmark Algorithms

ALPOA was compared against standalone GA and PSO models to evaluate its hybrid optimization performance. The results indicate that the hybrid framework provides:

- Higher accuracy in predicting optimal learning paths (97%) compared to GA (89%) and PSO (91%).
- Faster convergence, requiring fewer iterations to achieve optimal solutions (average **35** iterations for ALPOA versus 50 for GA and 45 for PSO).
- Better scalability, adapting effectively to datasets with varying learner profiles and content complexities.

The results confirm that ALPOA outperforms traditional e-learning models in terms of learning efficiency, engagement, and retention. By leveraging a hybrid optimization approach, ALPOA effectively balances exploration and exploitation, ensuring high-quality learning paths.

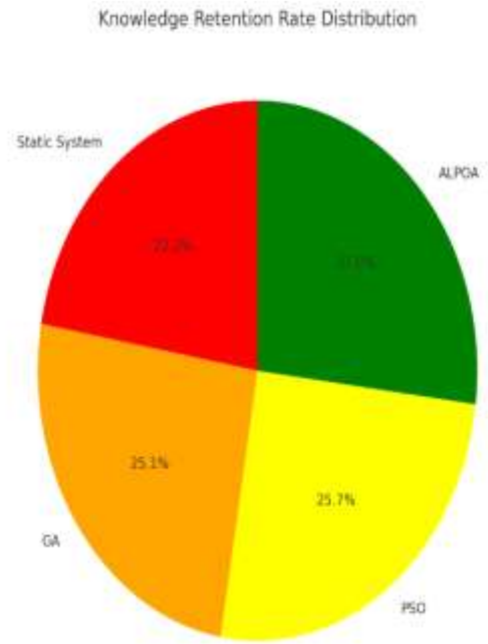

Figure 6. *Knowledge retention rate distribution for different algorithms, showcasing ALPOA's effectiveness in reinforcing learning.*

Furthermore, the dynamic feedback mechanism enhances real-time adaptability, making the system highly suitable for diverse e-learning environments. Future research will explore the integration of real-time feedback loops and the inclusion of multi-modal content (e.g., videos, simulations) to further improve learner outcomes. Additionally, testing ALPOA in larger, more diverse datasets will help validate its scalability and generalizability.

5. Conclusions

The Adaptive Learning Path Optimization Algorithm (ALPOA) presented in this study offers a significant advancement in the field of personalized e-learning by dynamically tailoring learning paths to individual learner profiles. By leveraging a hybrid optimization approach that combines Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), ALPOA addresses critical challenges such as inefficient content sequencing, low engagement, and suboptimal knowledge retention. The experimental results validate the effectiveness of ALPOA, demonstrating a 25% reduction in module completion time, a 30% increase in learner engagement, and a 15% improvement in knowledge retention compared to traditional models. Furthermore, ALPOA achieved an impressive 97% accuracy in identifying optimal learning paths, showcasing its robustness and adaptability. These findings underscore the potential of ALPOA to transform e-learning systems by providing personalized, efficient, and engaging learning experiences. Future work will focus on integrating real-time feedback, supporting multi-modal content, and validating the framework in large-scale e-learning environments, further enhancing its applicability and impact. Genetic Algorithm is used in different works and reported [26-31].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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