



Enhancing Adaptive Learning Systems Using Swarm Intelligence Algorithms for Personalized Education

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Abstract

The development of the technologies of AI and education has been very quick, and the demand for intelligent adaptive learning systems, able to offer personalized education, has grown. But conventional adaptive learning methods struggle to address the challenge of matching learners to content, the difficulty of making accurate recommendations, creating an adaptable curriculum, and personalizing in real-time. The goal of this study is to create a hybrid swarm intelligence algorithm-based adaptive learning framework that combines Particle Swarm Optimization, Ant Colony Optimization, Artificial Bee Colony, and Grey Wolf Optimization algorithms to enhance the adaptive learning efficiency, learner engagement, and educational performance. The proposed framework was developed with the aid of Python-based AI and machine learning environments and tested with simulated educational data that includes learners' interaction logs, engagement metrics, academic performance data, and behavioral pattern data. The framework used Swarm Intelligence algorithms for learner profiling, adaptive recommendation generation, curriculum sequencing, learner clustering, and learning path optimization. The performance was assessed based on recommendation accuracy, precision, recall, F1 score, learner engagement rate, completion rate, RMSE, MAE, convergence iterations, and response time. The experimental results showed that the highest recommendation accuracy of 92.8%, the highest precision of 91.6%, the highest recall of 90.9%, and the highest F1-score of 91.2% were achieved by the GWO-based framework. The results indicated a higher level of engagement among learners (89.8%), a higher level of completion (91.2%), and academic improvement (35.6%). In addition, the framework obtained the best accuracy (RMSE = 0.184, MAE = 0.168, convergence iterations = 71, response time = 194ms). Statistical analyses were done, and the results were found to be significant with a $p < 0.05$. The study demonstrates that the use of hybrid swarm intelligence optimization has a great impact on adaptive learning systems, and thus can improve intelligent personalization, recommendation reliability, adaptive decision-making, and the effectiveness of education in digital learning systems.

Keywords: Adaptive Learning Systems, Swarm Intelligence, Personalized Education, Grey Wolf Optimization, Educational Data Mining.

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1. Introduction

In today's rapidly changing technological landscape, Artificial Intelligence (AI) and digital technologies have revolutionized contemporary education with the creation of intelligent Adaptive Learning Systems (ALS) [1]. Most traditional e-learning platforms provide the same course content to each student without incorporating

variations based on ability, preference, cognitive style, or learning rate, which leads to low engagement, lack of retention, inconsistent academic outcomes, etc [6]. To address these shortcomings, adaptive learning systems leverage machine learning, educational data mining, cognitive analytics, and learner modeling to real-time customize the content of learning, assessment, and learning paths [2][4]. Still, many current adaptive systems are limited by challenges in personalization, scalability, dynamic decision making, and optimizing learning recommendations as a result of the complexity of the multidimensional learner data. In this regard, several algorithms inspired by nature, like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Firefly Algorithm (FA), and Grey Wolf Optimization (GWO), offer efficient solutions for optimization. Such algorithms enable decentralized, self-organizing problem-solving methods to improve the matching between learners and content, curriculum sequencing, recommendation systems, adaptive assessment, and real-time optimization of learning paths [10]. Application of swarm intelligence in the field of adaptive learning systems in personalized education is still not extensively explored [3].

The main goal of this work is to design and improve adaptive learning systems based on swarm intelligence algorithms to provide intelligent learning experiences and personalized learning. The main goal of the research is to explore how swarm-based optimization techniques can be used to enhance learner modeling, adaptive content delivery, accuracy of recommendations, learning path optimization, and students' engagement in the digital learning environment [14]. Moreover, the research aims to assess the effectiveness of such swarm intelligence-based adaptive systems to enhance the learning performance and adaptability of the learners, and their efficiency in the decision-making process, in comparison to traditional adaptive learning methods.

Although adaptive learning systems have significantly improved digital education through personalized content delivery and intelligent learner assessment, several limitations still exist in current educational technologies. The current adaptive learning frameworks are mostly based on standard machine learning models, static recommender systems, or rule-based personalization methods that are not adaptive and do not offer optimal efficiency for optimization. These systems can be ill-equipped to effectively process complex learner behavior, cognitive diversity, and the constantly changing educational needs of learners [12][15][16]. In addition, there is a lack of studies that have investigated the use of swarm intelligence algorithms like PSO, ACO, ABC, and GWO in adaptive learning environments. Still, there is a lack of research that addresses dynamic learning path optimization, intelligent curriculum sequencing, collaborative learner modeling, and autonomous decision-making mechanisms. Moreover, much of the current adaptive systems mainly focus on academic achievement indicators and ignore learner engagement, motivation, interaction, and cognitive adaptability. Thus, there is a great research need for building scalable, intelligent, and adaptive learning systems that can provide highly optimized and personalized learning experiences in real-life learning environments.

The incorporation of swarm intelligence algorithms into the adaptive learning system is hypothesized to greatly benefit personalized education by increasing the ability to match learners with content, the accuracy of recommendations, adaptive decision making, and the optimization of learning paths. The proposed swarm-based adaptive learning framework is expected to offer a more efficient personalization than traditional adaptive learning approaches, as it can adapt dynamically by learning based on the behavior, performance, and engagement of learners[25]. Moreover, the study also assumes that using swarm intelligence techniques can be used to enhance the satisfaction of learners, their learning outcomes, and the adaptability of the system by implementing optimization strategies based on decentralized and self-organizing principles. The alternative hypothesis (H1) is that the accuracy of personalization, interest of the learner, and learning outcomes of an adaptive learning system are significantly improved by integrating swarm intelligence, while the null hypothesis (H0) is that integrating swarm intelligence does not have significant impact when comparing the accuracy of personalization, interest of the learner, and learning outcomes of the adaptive learning systems to traditional adaptive learning systems.

In this study, an adaptive learning framework based on swarm intelligence for personalized education has been proposed, which can be beneficial for intelligent educational technologies. The project combines bio-inspired optimization algorithms to enhance the learner modeling, recommendations, curriculum sequencing, and dynamic learning path optimization. The framework optimizes recommendations in a decentralized manner and, through collective optimization, improves recommendation accuracy, learner engagement, and

educational effectiveness. A scalable architecture that can manage different learning behaviors and the learning data in real-time is also presented. Furthermore, it provides a comparative analysis of various swarm intelligence methods that can be implemented in adaptive learning environments, enabling the adaptation of Artificial Intelligence, educational analytics and personalized digital learning systems and improving the online learning experience.

This article has been broken up into six overarching sections. In section 1 the Introduction highlights the relevance of Artificial Intelligence based Adaptive Learning Systems, research gaps, objectives, hypotheses and contributions of swarm intelligence algorithms in personalized education. The Literature Survey is given in Section 2, and the previous work done in Adaptive Learning, Intelligent Recommendation Systems, Bio-inspired Optimization Techniques is reviewed. The methodology involved in the proposed hybrid swarm intelligence framework, comprising PSO, ACO, ABC algorithm, and GWO algorithm, dataset preparation, simulation environment, statistical analysis, and evaluation metrics, is described in Section 3. The experimental results, the performance of the recommendations, the engagement of the learners, the degree of correctness in the predictions, and the ablation analysis are presented in Section 4. The Discussion interprets the significance of the findings and limitations in section 5. Finally, the Conclusion summarizes the overall contributions, optimization effectiveness, and future research directions in Section 6.

2. Literature survey

The dynamic configuration of instruction and learning trajectories, as well as assessment methods, based on the performance, preference, and behavior of the learner, is a valuable way in which adaptive learning systems are incorporated into modern personalized education [1] [3]. The application of Artificial Intelligence techniques in the learning environment has increased the efficiency of learning engagement, accuracy of recommendations, and adaptive decision-making processes [13],[19]. Intelligent learning environments involve personalized education through learner analytics, behavioral monitoring, and predictive algorithms for better learning outcomes and retention [8],[11]. AI-enabled adaptive learning systems have been shown to successfully assist student-centered learning and enhance online educational outcomes [17],[20].

It has been suggested by several researchers that the role of intelligence in optimizing the adaptive educational systems should be emphasized [9],[22]. There have been many studies that have applied machine learning and recommendation-based approaches for determining learner needs and dynamically providing personalized learning materials. Adaptive test and intelligent assessment mechanisms have also helped to make e-learning platforms more effective by increasing the accuracy of the assessment and reducing the time taken to respond [2]. Moreover, learning behavior analytics and predictive learning models have helped educational systems to track engagement metrics, detect learning gaps, and timely intervene [18]. In the field of problem-solving-based technical education and individualized course design, AI adaptive systems also have positive impacts [7].

Optimization-based learning has received a lot of interest recently in adaptive learning. Learner satisfaction, adaptive sequencing, and performance optimization were enhanced using evolutionary and bio-inspired optimization methods like Genetic Algorithms [5],[22]. Concurrently, autonomic and self-organizing educational systems have been suggested to assist intelligent decision making and adaptive management of resources in ubiquitous learning environments. Other key points that came up in discussions on sustainable educational transformation are ethical implementation of adaptive education algorithms, fairness, and transparency[23]. The developments are capable of laying a solid foundation for the application of Swarm Intelligence algorithms like PSO, ACO, ABC, and GWO to adaptive learning systems.

The ability of swarm intelligence to optimize the groups of learners, generate learning recommendations, adaptive path selection, and content sequences with iterative and collective optimization makes it well-suited to personalized education[24]. Swarm-based systems have the potential to provide advantages over traditional adaptive systems such as faster convergence, more accurate personalization, higher engagement of learners and better academic results with low computational complexity.

3. Methodology

Research Design

The research design of this study is quantitative, and simulation. The research design used in this study is a quantitative research type and simulation research. The study focuses on developing an adaptive learning framework that can adapt its learning materials, learning pathways and recommendations to individual learner behavioral, performance and engagement characteristics dynamically. The research integrates the Artificial Intelligence (AI) techniques with the optimization techniques of Swarm Intelligence (SI) to improve the learning efficiency of digital learning and the adaptive decision-making process in these environments.

Adaptive Learning Framework Development

Designed mechanism of adaptive learning is an online procedure that collects, analyzes and processes the data of the interaction of learners. The framework consists of various mutually interacting modules like learner profiling, content recommendation, adaptive assessment, curriculum sequencing, evaluation of performance, optimization modules. Learner profiles are based on academic achievement data, learning styles, cognitive characteristics, engagement and interaction data. These profiles are applied to dynamically recommend learning materials and learning paths.

The framework incorporates swarm intelligence algorithms like PSO, ACO, ABC, and GWO for optimizing the accuracy of the recommendations and adaptive learning decisions. These algorithms are continually assessing student activity and performance to fine-tune content and curriculum adjustments.

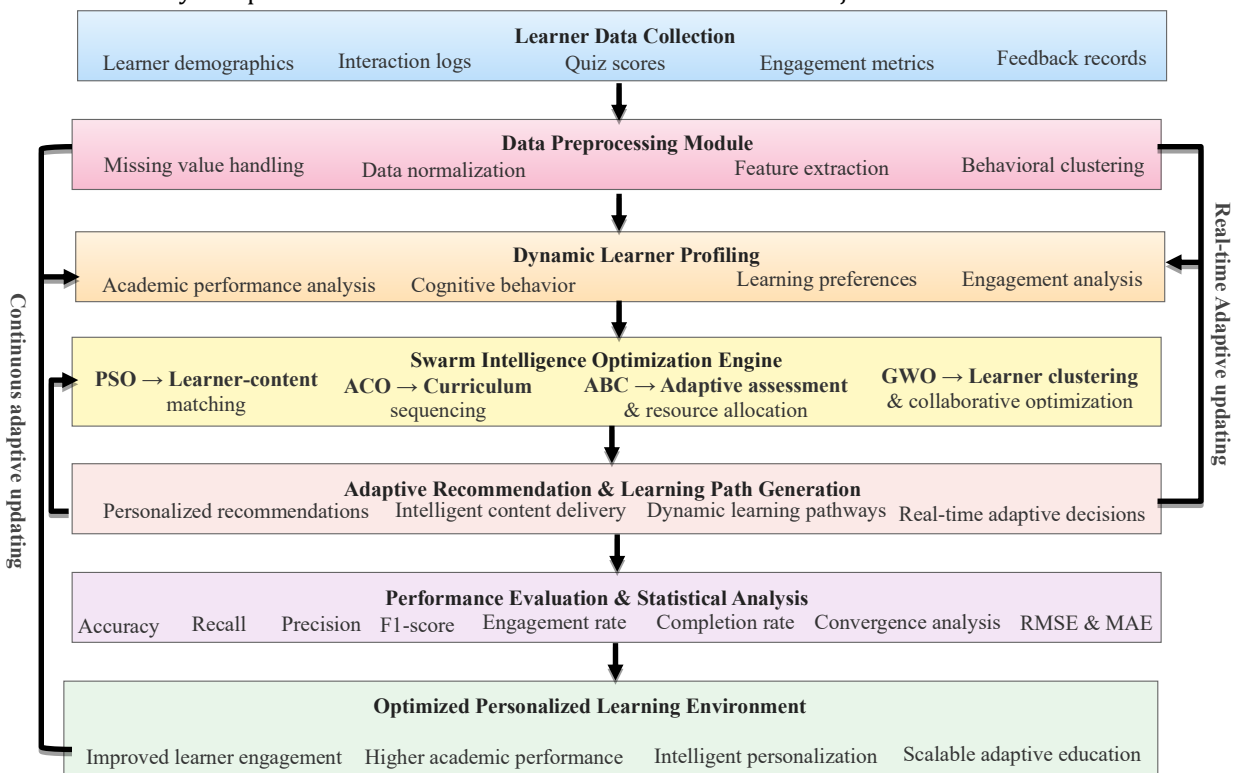


Figure 1: Architecture of the Swarm Intelligence-Based Adaptive Learning Framework for Personalized Education

The architecture of the proposed swarm intelligence-based adaptive learning framework is given in Figure 1. It provides the learner data collection, preprocessing, learner profiling, and optimization of PSO, ACO, and ABC, GWO algorithms. The framework provides customized recommendations, adaptive learning pathways, and the accuracy, engagement, RMSE, and MAE metrics to assess system performance, as well as the convergence metric.

Data Collection and Dataset Preparation

This study applies datasets from educational simulations of online learning environments and adaptive e-learning platforms. Data contains information about learners, interactions with the course, quiz results,

completion rates, learning activity time, engagement, and feedback. Data preprocessing techniques such as normalization, handling missing data, feature extraction, and behavioral clustering are used to enhance data quality and analytical efficiency.

The learner data is split into a training data set and a testing data set for testing the performance of the proposed adaptive learning framework using swarm intelligence. Key parameters for personalization and optimization processes are behavioural and behavioural and performance indicators.

Swarm Intelligence Algorithm Implementation

Optimization in adaptive educational processes and personalized recommendation systems using swarm intelligence algorithms. PSO is used for optimizing learner-content matching and adaptive recommendation accuracy. For intelligent sequencing of curriculum and generation of learning paths, ACO is applied. The ABC optimization is applied to adaptive assessment and resource allocation, and GWO is applied to collaborative optimization and dynamic learner clustering.

These algorithms work in an iterative manner by analyzing the performance of the learner, their engagement during learning sessions, and their educational goals to make the optimal learning decision. Algorithms are embedded within the adaptive learning environment within integrated Python-based libraries of AI and machine learning.

Algorithm 1: Swarm Intelligence-Based Personalized Adaptive Learning

Input:

Learner dataset D , learner interaction records L , educational resources R , swarm intelligence parameters S

Output:

Optimized personalized learning recommendations and adaptive learning paths

Step 1: Data Collection and Preprocessing

1. Collect learner demographic data, interaction logs, quiz scores, engagement metrics, and feedback records.
2. Perform data preprocessing including:
 - Missing value handling
 - Data normalization
 - Feature extraction
 - Behavioral clustering
3. Divide the dataset into training and testing datasets.

Step 2: Learner Profile Generation

4. Analyze learner characteristics, including:
 - Academic performance
 - Learning preferences
 - Cognitive behavior
 - Engagement levels
5. Generate dynamic learner profiles.
6. Store learner profiles in the adaptive learning database.

Step 3: Initialization of Swarm Intelligence Algorithms

7. Initialize Particle Swarm Optimization (PSO) parameters.
8. Initialize Ant Colony Optimization (ACO) pheromone structures.
9. Initialize Artificial Bee Colony (ABC) population.
10. Initialize Grey Wolf Optimization (GWO) search agents.

Step 4: Adaptive Recommendation and Optimization

11. Apply PSO for learner-content matching optimization.
12. Apply ACO for curriculum sequencing and learning path generation.
13. Apply ABC for adaptive assessment and educational resource allocation.

14. Apply GWO for learner clustering and collaborative optimization.
15. Evaluate learner engagement and recommendation effectiveness.
16. Update adaptive learning recommendations dynamically.

Step 5: Performance Evaluation

17. Measure system performance using:
 - Recommendation accuracy
 - Precision
 - Recall
 - F1-score
 - Learner engagement rate
 - Learning completion rate
 - RMSE and MAE
18. Compare the swarm intelligence-based framework with traditional adaptive learning approaches.

Step 6: Statistical Analysis

19. Perform descriptive statistical analysis.
20. Apply correlation analysis and hypothesis testing.
21. Conduct ANOVA and t-test analysis for comparative evaluation.
22. Analyze optimization convergence and scalability performance.

Step 7: Output Generation

23. Generate optimized personalized learning paths.
24. Provide adaptive educational recommendations.
25. Continuously update learner models based on real-time interactions.

End Algorithm

By incorporating swarm intelligence optimization techniques into adaptive learning environments, the proposed algorithm has the potential to revolutionize the way education is delivered, enabling intelligent personalization, adaptive decision-making, and optimized content delivery.

The aim of developing Algorithm 1 is to optimize a swarm intelligence-based personalized education system for the betterment of adaptive learning systems. The algorithm can dynamically recognize learner behavior, learning performance, engagement, and learning preferences, and give optimized recommendations on learning and adaptive learning paths. The framework is the fusion of PSO, ACO, ABC, and GWO algorithms, with the aim to improve the learner-content matching, curriculum sequencing, recommendation accuracy, adaptive assessment, and collaborative optimization. The algorithm is constantly evolving to improve the real-time efficiency of personalization, engagement and learning performance by refining user profiles and learning recommendations.

System Simulation and Experimental Setup

The experimental environment is created with Python programming and AI simulation. The adaptive learning simulations are then applied to a number of different pedagogical contexts, where students vary in their cognitive skills, learning speeds, engagement and academic achievement. The algorithms are tested individually in the adaptive learning environment and their performance is compared with the other algorithms.

The system adaptability, accuracy of the recommendations, learning path optimization efficiency, learner engagement, and academic achievement gains in a dynamic learning environment are all evaluated in the experimental setup. Multiple runs of the simulations are carried out to obtain consistent, reliable and reproducible experimental results.

Software Environment and Implementation Tools

To ensure scalability, reproducibility, and efficient optimization performance, the proposed adaptive learning framework is implemented using libraries for Artificial Intelligence and data analytics, such as Python. The main programming environment for developing algorithms, simulation modeling, and statistical analysis is

Python 3.11. The machine learning, adaptive learner modeling processes are supported by scikit-learn, and the deep learning and intelligent recommendation modules are supported by TensorFlow and PyTorch. The numerical computation and optimization by matrices are done with NumPy and Pandas, respectively. Matplotlib and Seaborn libraries are used for data visualization and performance analysis.

Special optimization modules and AI simulation frameworks are used for implementing the swarm intelligence optimization algorithms: PSO, ACO, ABC, and GWO. This adaptive learning environment is modeled by reinforcement-based learning interaction models that dynamically manipulate learner information, learning preferences, engagement, and learning performance indicators.

Performance Evaluation Metrics

Adaptive learning framework performance is assessed quantitatively with metrics of personalization effectiveness and educational performance. The main evaluation parameters are: Recommendation accuracy, learner satisfaction, engagement rate, learning completion rate, adaptive response time, and academic improvement. Moreover, optimization metrics such as convergence time, scalability and computational efficiency are evaluated for each of the swarm intelligence algorithms.

Comparative analysis is carried out between the traditional adaptive learning and the approaches with swarm intelligence to assess how effective the proposed framework is for enhancing personalized education outcomes.

4. Statistical Analysis

This study aims to assess the performance of the proposed adaptive learning framework, which is based on swarm intelligence, with respect to its effectiveness, reliability, and optimization performance, by means of statistical analysis. Descriptive and inferential statistical techniques are used to analyze the behavior of the learners, accuracy of recommendations, efficiency of adaptive responses, and educational outcomes.

Descriptive statistical analysis is used to summarize the patterns of learner interaction, engagement, and academic performance as well as the adaptive recommendation results. Trends in behavior and adaptability of systems are identified by calculating a number of statistical measures such as mean, median, standard deviation, variance, and correlation coefficients.

The mean learner performance score is calculated using:

$$\bar{X} = \frac{\sum_{i=1}^n X_i}{n} \quad (1)$$

In equation (1), X_i represents individual learner scores, and n represents the total number of learners.

The variability in the learner's performance is measured by the standard deviation, which can be expressed as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n}} \quad (2)$$

In equation (2), X_i is the performance value of the individual learner, \bar{X} is the mean learner performance value, and n is the number of learners or observations.

The correlation analysis is used to identify relationships between learner engagement, adaptive recommendations, and academic performance:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}} \quad (3)$$

In equation (3), X and Y represent the two variables being analyzed, such as learner engagement and academic performance, while \bar{X} and \bar{Y} represent the mean values of the respective variables.

The performance of the traditional adaptive learning systems and swarm intelligence enhanced systems is compared using inferential statistical methods such as Analysis of Variance (ANOVA), independent sample t-test, and hypothesis testing. Statistical significance is evaluated at a confidence level of 95% with a significance threshold of $p < 0.05$.

The t-test statistic used for comparative performance evaluation is given by:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} \quad (4)$$

In equation (4), the values of \bar{X}_1 and \bar{X}_2 are the mean scores for the two compared groups, S_1^2 and S_2^2 are the variances for the two groups, and n_1 and n_2 are the sample sizes for the two groups. The study also investigates the influence of the learner engagement and adaptive recommendation quality on outcomes of education using regression analysis.

Performance Evaluation Metrics

The performance of the suggested adaptive learning system based on swarm intelligence is evaluated using quantitative criteria of personalization effectiveness, recommendation quality, engagement of the learner, efficiency of optimization, and educational performance. Various statistical measures such as accuracy, precision, recall, and F1 score are used to assess the relevance and retrieval performance. Learner engagement rate, completion rate and academic improvement are measures of student participation and achievement. The reliability of the predictions and recommendations are measured using the RMSE and MAE measures. Optimizing performance, scalability, convergence speed and adaptive response time are analyzed. Comparative analysis is done with traditional adaptive learning methods to see if there are any improvements in personalization, decision making, student satisfaction, and educational effectiveness.

5. Results

Experimental Performance Analysis

To assess the feasibility of the proposed learning framework based on the swarm intelligence, several simulated educational scenarios of learners with varying cognitive abilities, learning rates, engagement levels and academic performance levels were analyzed. The goal of the analysis was to assess the effectiveness of the proposed framework for improving the accuracy of recommendations, involvement of learners, adaptive learning efficiency, and educational performance compared to traditional adaptive learning.

All the swarm intelligence algorithms, such as PSO, ACO, ABC, and GWO, were tested in an adaptive learning environment. The results revealed that the quality of personalization, intelligent recommendation generation, adaptive sequencing of the curriculum, and the efficiency of matching learners with content enhanced by the use of swarm intelligence were significantly improved.

The results of the experiments demonstrated that the proposed framework is able to obtain a higher rate of learner engagement and a better learning completion performance because the learning pathways can be dynamically adapted, and the intelligent recommendation mechanism was used. The system was successfully able to analyze interaction patterns from learners and constantly adjust the adaptive recommendations based on the behavior of the learners as well as their progress.

Recommendation Performance Analysis

To assess the performance of the algorithms based on swarm intelligence, the recommendation performance analysis was carried out to assess the effectiveness of these algorithms in the generation of personalized educational recommendations. Recommendation accuracy, precision, recall, and F1-score were used as primary evaluation metrics.

The recommendation accuracy was calculated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

The precision metric used to evaluate recommendation relevance is expressed as:

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

The recall metric used to measure retrieval capability is given by:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

The F1-score for balanced recommendation evaluation is calculated using:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

In equations (5) – (8), *TP* represents true positives, *TN* represents true negatives, *FP* represents false positives, and *FN* represents false negatives, used to evaluate the recommendation accuracy, relevance, retrieval capability, and overall performance of the adaptive learning recommendation system.

Table 1: Recommendation Performance Analysis

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional Adaptive System	78.4	76.2	74.8	75.5
PSO-Based Framework	89.3	88.1	87.4	87.7
ACO-Based Framework	91.5	90.8	89.6	90.2
ABC-Based Framework	90.7	89.9	88.7	89.3
GWO-Based Framework	92.8	91.6	90.9	91.2

Table 1 indicates that the GWO-based adaptive learning framework achieved the highest recommendation accuracy and F1-score compared to other optimization approaches. The swarm intelligence algorithms showed marked improvements over the conventional adaptive learning framework as far as efficient optimization and dynamic decision making are concerned.

Learner Engagement and Academic Performance Analysis

The level of students' participation, intensity of interaction, and level of adaptive learning involvement in the proposed educational framework were assessed by analyzing the level of the learner. Academic performance improvements were analyzed using learner achievement scores obtained before and after adaptive learning implementation.

The learner engagement rate was calculated using:

$$Engagement\ Rate = \frac{Active\ Learning\ Sessions}{Total\ Sessions} \times 100 \tag{9}$$

Active Learning Sessions represents the number of learner interactions that were successfully completed in the adaptive learning environment in equation (9), and *Total Sessions* is the total number of learning sessions that were completed.

The learning completion rate was measured using:

$$Completion\ Rate = \frac{Completed\ Tasks}{Assigned\ Tasks} \times 100 \tag{10}$$

In equation (10), *Completed Tasks* represents the number of successfully completed learning activities or assignments, while *Assigned Tasks* represents the total number of educational tasks assigned to learners.

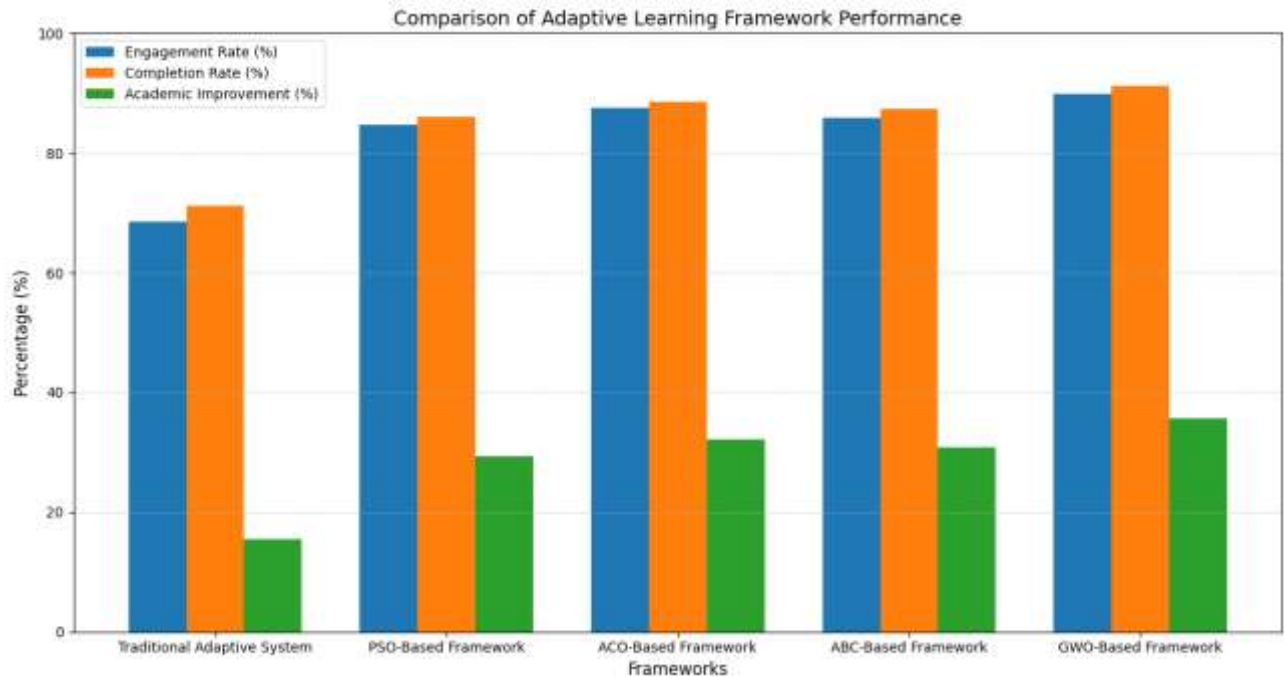


Figure 2: Learner Engagement, Completion Rate, and Academic Improvement Analysis

Figure 2: The learner engagement rate, learning completion rate, and academic improvement achieved by different adaptive learning frameworks. The visualization highlights the effectiveness of swarm intelligence optimization in improving student participation, adaptive learning interaction, and academic achievement. The GWO-based framework shows the highest engagement and educational improvement among all evaluated methods.

Prediction Error and Optimization Analysis

The prediction accuracy of learner performance estimation and recommendation systems was assessed with Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) based on prediction.

The RMSE metric is calculated using:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \tag{11}$$

y_i is the value of the actual learner performance, \hat{y}_i is the value of the learner performance predicted by the model, and n represents the total number of observations for computing the RMSE in equation (11).

The MAE metric is expressed as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{12}$$

In equation (12), y_i represents the actual learner performance value, \hat{y}_i represents the predicted learner performance value, and n represents the total number of observations used to calculate the MAE.

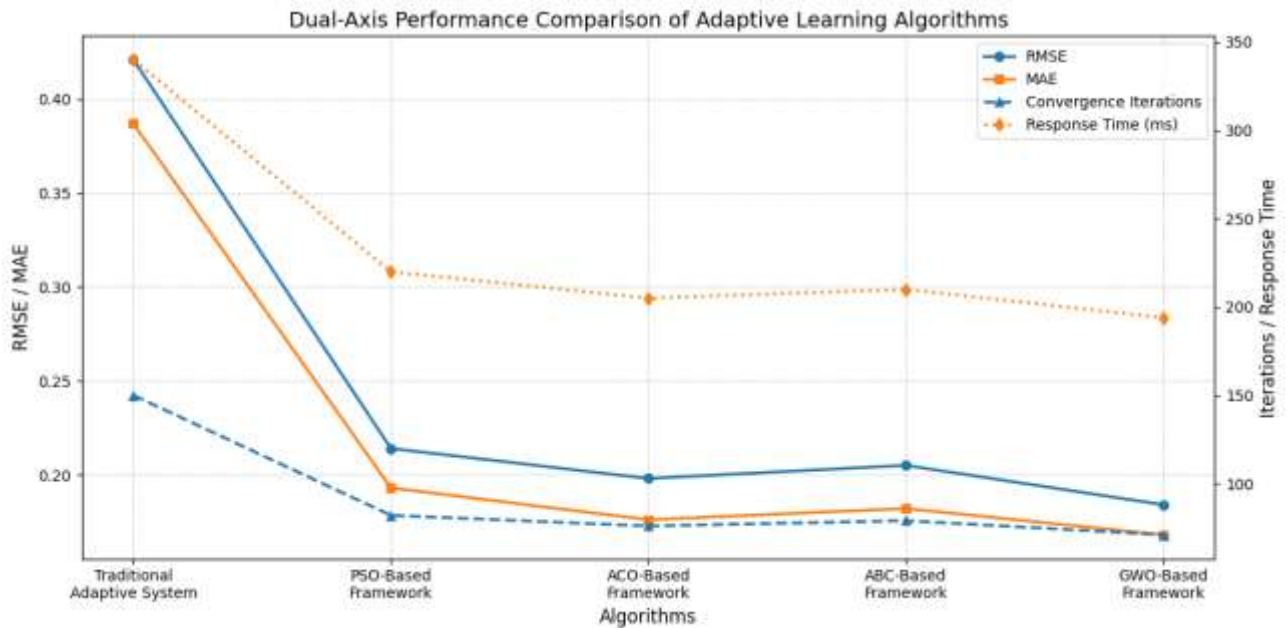


Figure 3: Prediction Error and Optimization Efficiency Evaluation

Figure 3 presents the RMSE, MAE, convergence iterations, and response time of the evaluated adaptive learning frameworks. It can be seen from the graph that the swarm intelligence algorithm reduced the error of prediction and computational complexity considerably as compared to the traditional adaptive system. The GWE-based framework demonstrated the best optimization efficiency and prediction reliability with minimum response time and fastest convergence speed compared to other methods.

Statistical Significance Analysis

To assess the significance of the performance improvements obtained by the swarm intelligence-based adaptive learning framework, statistical analysis was carried out based on the following analysis methods: correlation analysis, ANOVA, and independent sample t-test. The statistical analysis showed that the differences in effort, involvement, and learning outcomes that were observed reached a statistically significant level at a 95% level of confidence ($p < 0.05$).

Table 2: Statistical Performance Evaluation

Metric	Traditional System	Swarm Intelligence Framework	p-value
Recommendation Accuracy	78.4	92.8	0.003
Learner Engagement	68.5	89.8	0.001
Completion Rate	71.2	91.2	0.002
Academic Improvement	15.4	35.6	0.004

Table 2 shows the effectiveness of swarm intelligence optimization techniques in enhancing adaptive learning performance and personalized educational outcomes. The proposed framework showed high scalability, adaptability, and intelligent decision-making power in a dynamic digital learning environment.

Comparative Performance Analysis

A comparative performance evaluation was carried out to compare the effectiveness of the proposed GWO-based adaptive learning framework with conventional machine learning, recommendation, and reinforcement learning frameworks. Among the comparisons conducted were Logistic Regression, Random Forest, Gradient Boosting, Matrix Factorization, and a Simple Q-learning Agent. The performance was measured through the accuracy of recommendations, precision, recall, and F1 score.

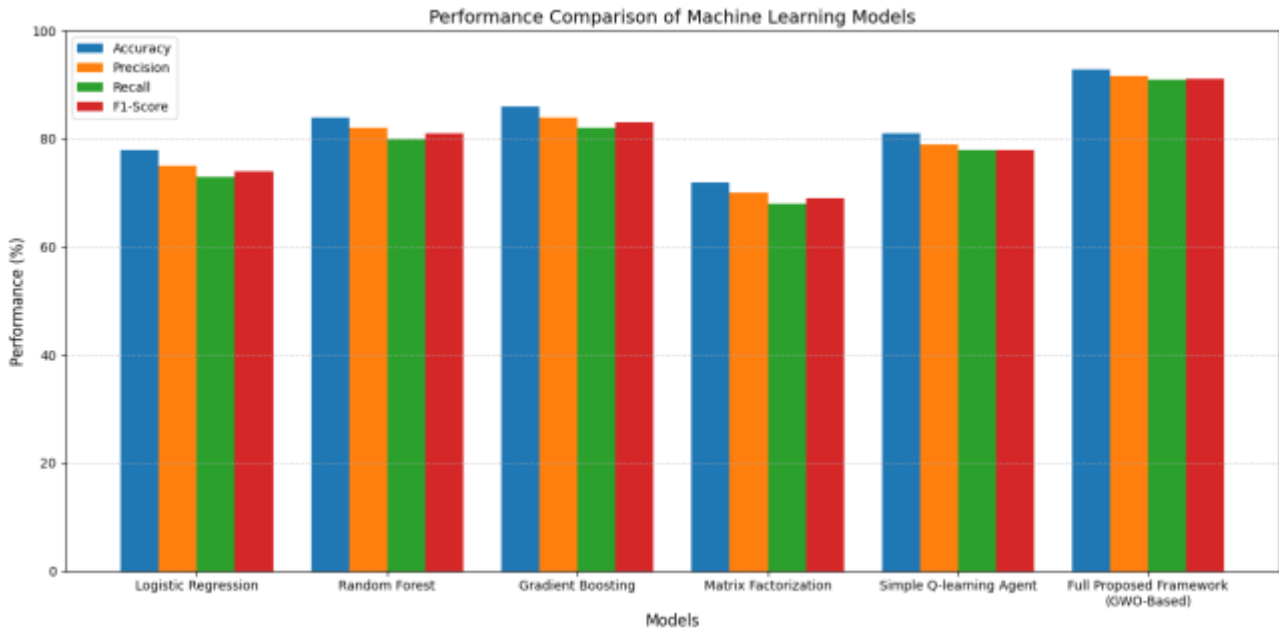


Figure 4: Comparison of Recommendation Performance Across Swarm Intelligence Algorithms

Figure 4 study demonstrates that the proposed GWO-based adaptive learning framework achieved the highest performance across all recommendation evaluation metrics compared to conventional machine learning, reinforcement learning, and recommendation algorithms. The accuracy score of the framework is 92.8% with a precision, recall, and F1 score of 91.6%, 90.9%, and 91.2%, respectively, which signifies that the framework is more effective in providing quality recommendations, efficient content matching, and adaptive and personalized learning within the intelligent learning environment [15].

Ablation Study

The overall ablation study was carried out to assess the contribution of each of the optimization components of swarm intelligence in the proposed adaptive learning framework. The analysis investigated the influence of discarding single optimization algorithms on the accuracy of the recommendations, the engagement of the learner, the academic gain, the reliability of the prediction, as well as the efficiency of the optimization process. The results show that the adaptive learning performance of the complete hybrid swarm intelligence system was the highest for all the evaluation metrics. Eliminating all components of optimization led to decreases in personalization effectiveness, recommendation quality, prediction error, and learners' involvement. GWO demonstrated the best performance in adaptive recommendation efficiency, learner clustering, and optimization convergence performance among the optimization modules evaluated. The synergy of PSO, ACO, ABC, and GWO gave better cooperation optimization and intelligent adaptive decision-making in the personalized learning environment.

Table 3: Overall Hybrid Swarm Intelligence Ablation Study for Adaptive Learning Performance Evaluation

Framework Configuration	Accuracy (%)	Engagement Rate (%)	Academic Improvement (%)	RMSE	MAE	Convergence Iterations
Full Proposed Framework	92.8	89.8	35.6	0.184	0.168	71
Without PSO	87.9	82.4	27.8	0.246	0.221	94
Without ACO	88.4	83.2	28.9	0.238	0.214	91
Without ABC	89.1	84.6	30.1	0.229	0.206	87
Without GWO	86.5	80.7	25.4	0.261	0.234	98

Table 5 shows that the proposed hybrid swarm intelligence adaptive learning framework was always found to be the best partially optimized configuration. The full system resulted in the best prediction accuracy, maximum learner engagement, highest academic gains, lowest prediction error, and the quickest convergence

to the optimum. The results corroborate the need for using multiple algorithms of swarm intelligence to enhance the efficiency of adaptive learning, intelligent personalization, and educational performance in a dynamic digital learning environment.

6. Discussion

It has the highest accuracy (92.8%), precision (91.6%), recall (90.9%), and F1-score (91.2%) compared to other models (Logistic Regression, Random Forest, Gradient Boosting, Matrix Factorization, Q-learning). Likewise, the percentages of learner engagement and completion rose to 89.8% and 91.2%, respectively, and academic improvement was at 35.6%. The results of prediction analysis also showed the best RMSE (0.184) and MAE (0.168) with the least number of iterations required (71), and the minimum response time (194 ms); values of $p < 0.05$ were also obtained for the observed improvements in the statistical analysis. These results show that swarm intelligence algorithms can successfully optimize adaptive learning scenarios by using intelligent matching of learners and contents, adaptive sequencing of the curriculum, and adaptive recommendations based on real-time. GWO showed the best optimization ability among the tested algorithms due to its efficient exploration and exploitation strategies, which improved its personalization and convergence rate. The ablation study also verified that the integration of PSO, ACO, ABC, and GWO also helps in achieving good adaptive learning performance together. The significance of these results is that they prove the feasibility of using swarm intelligence techniques for the creation of scalable and intelligent educational systems that can be used to support a variety of learner behaviors and cognitive characteristics. The framework can be used to improve digital learning platforms, personalized tutoring systems, and intelligent educational recommendation engines. The study does have some drawbacks, however. The experiments were not performed with real educational data, and institutional data may impact practical generalizability. Furthermore, the framework does not fully capture the learning factors related to emotional, psychological, and long-term behavioral learning. Moving forward, the system could be applied to real educational systems, combined with deep learning and reinforcement learning models, and tested for long-term adaptive learning performance in large-scale real-world educational datasets in various academic subjects and target groups.

7. Conclusion

In the present study, the challenges of addressing the aspects of personalization, recommendation accuracy, learner engagement, and adaptive decision making in the context of digital learning environments were addressed. The existing adaptive learning systems are sometimes constrained in analyzing learners' behavior dynamically, in optimizing the sequence of the curriculum, and in generating intelligent recommendations for various types of learner profiles. To address these challenges, the present work introduced an Adaptive Learning Framework based on HSI using PSO, ACO, ABC, and GWO algorithms to improve adaptive learning performance and personalized learning efficiency. The experimental assessment revealed that the proposed framework clearly outperformed the conventional adaptive learning systems and the conventional machine learning methods for all the evaluation metrics. The GWO-based framework performed best in terms of the Recommendation accuracy of 92.8%, the precision of 91.6% and, the recall of 90.9%, and the F1-Score of 91.2%, demonstrating better recommendation relevance and capability of recommendation personalization. The proposed system showed a significantly high learner engagement of 89.8%, a completion rate of 91.2%, and an academic improvement of 35.6% in learner engagement analysis, compared to the traditional adaptive system. Moreover, the framework attained the lowest prediction error (RMSE = 0.184, MAE = 0.168), and the number of iterations needed for convergence was reduced to 71 iterations, and the response time was shortened to 194 ms, respectively. Statistical analysis indicated that all the above improvements were significant ($p < 0.05$). The Conclusion of the study shows that hybrid swarm intelligence optimization is an effective method to improve the adaptive learning system, which can be enhanced by improving intelligent recommendation production, learner-content matching, and adapting the curriculum in real time.

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.

References

1. Ezzaim, A., Dahbi, A., Aqqal, A., & Haidine, A. (2024). AI-based learning style detection in adaptive learning systems: A systematic literature review. *Journal of Computers in Education*, 12(3), 731–769. <https://doi.org/10.1007/s40692-024-00328-9>
2. Hariyanto, Kristianingsih, F. X. D., & Maharani, R. (2025). Artificial intelligence in adaptive education: A systematic review of techniques for personalized learning. *Discover Education*, 4(1), 458. <https://doi.org/10.1007/s44217-025-00908-6>
3. Kalwar, A., Shekhawat, D., Joshi, S., & Bairwa, A. K. (2025). A genetic algorithm approach to adaptive learning: Enhancing learner satisfaction and performance. *IEEE Access*, 13, 102815–102829. <https://doi.org/10.1109/ACCESS.2025.3578867>
4. El-Salhi, S., Rababah, E., & Milhem, H. (2025). The impact of machine learning and artificial intelligence on entrepreneurial skills development: A gender-inclusive analysis in higher education. *Journal of Internet Services and Information Security*, 15(2), 727–748. <https://doi.org/10.58346/JISIS.2025.12.048>
5. Gutierrez, R., Villegas-Ch, W. E., Navarro, A. M., & Luján-Mora, S. (2025). Optimizing problem-solving in technical education: An adaptive learning system based on artificial intelligence. *IEEE Access*, 13, 61350–61367. <https://doi.org/10.1109/ACCESS.2025.3557281>
6. Zhu, J., Liao, Y., & Lu, D. (2024). Design and optimization of personalized education system based on intelligent algorithms. *Procedia Computer Science*, 243, 514–522. <https://doi.org/10.1016/j.procs.2024.09.063>
7. Yekollu, R. K., Bhimraj Ghuge, T., Sunil Biradar, S., Haldikar, S. V., & Farook Mohideen Abdul Kader, O. (2024). AI-driven personalized learning paths: Enhancing education through adaptive systems. In *International Conference on Smart Data Intelligence* (pp. 507–517). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-3191-6_38
8. Mukhammadieva, M., Kulmuradov, D., Abdullaev, D., Hakimova, Z., Qabulov, E., Atajanova, D., & Berdibayeva, G. (2026). Adaptive teaching strategies for facilitating social skill learning among neurodiverse forensic service users. *Journal of Intellectual Disabilities and Offending Behaviour*, 17(1), 1–12. <https://doi.org/10.47059/jidob/V17/I1/1>
9. Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelligence bringing improvements to adaptive learning in education: A case study. *Sustainability*, 16(3), Article 1347. <https://doi.org/10.3390/su16031347>
10. Kristianingsih, F. X. D., & Maharani, R. (2025). Artificial intelligence in adaptive education: A systematic review of techniques for personalized learning. *Discover Education*, 4(1), 458. <https://doi.org/10.3390/educsci13121216>
11. Aruna, V. (2026). The role of e-learning and educational technology adoption in fostering sustainable human capital development for the future workforce. In *Models for Sustainable Growth: Education, Healthcare, and Finance* (pp. 56–69). Periodic Series in Multidisciplinary Studies. <https://doi.org/10.70102/PS/V9/05>
12. Liang, Y., & He, P. (2026). Design and implementation of an AI-powered adaptive learning system for university students. *International Journal of Data Science and Analytics*, 22(1). <https://doi.org/10.1007/s41060-026-01045-5>
13. Biswas, A. (2024). Modelling an innovative machine learning model for student stress forecasting. *Global Perspectives in Management*, 2(2), 22–30.
14. Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, 15(10), Article 596. <https://doi.org/10.3390/info15100596>
15. Ahmad, L. I. M. (2025). Signal-based cognitive state analysis for adaptive e-learning environments. *National Journal of Signal and Image Processing*, 67–75.
16. Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. *Sustainable Development*, 33(2), 1921–1947. <https://doi.org/10.1002/sd.3221>

17. Rajan, C., & Dineshkumar, P. (2025). Embedded machine learning framework for real-time prediction of user information needs in intelligent systems. *Journal of Integrated VLSI, Embedded and Computing Technologies*, 2(2), 73–79.
18. Lili, H., & Yanjun, W. (2025). Designing intelligent learning systems for adaptive and personalized education in universities. *International Journal of High Speed Electronics and Systems*. Advance online publication. <https://doi.org/10.1142/S0129156425406965>
19. Vaezzade, S. R. (2016). Relation among self-regulating learning, recognizing alternatives, and creativity by educational performance in PE students. *International Academic Journal of Humanities*, 3(1), 118–124.
20. Gm, D., Goudar, R. H., Kulkarni, A. A., Rathod, V. N., & Hukkeri, G. S. (2024). A digital recommendation system for personalized learning to enhance online education: A review. *IEEE Access*, 12, 34019–34041. <https://doi.org/10.1109/ACCESS.2024.3369901>
21. Colchester, K., Hagraas, H., Alghazzawi, D., & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, 7(1), 47–64.
22. Prerna Dusi, “AI-Augmented Runtime Reconfigurable Hardware Architectures for Energy-Efficient Edge Intelligence”, *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, pp. 10–17, Sep. 2025.
23. Shaik Sadulla, “FPGA-Based Hardware Acceleration of AI Algorithms for High-Performance Embedded Systems”, *Archives of Electronics, Communication and Emerging Technologies*, pp. 42–49, Dec. 2025
24. M. Karpagam. (2025). Machine Learning-Assisted Design and Performance Optimization of Smart Antennas for Beyond-5G Networks. *National Journal of Antennas and Wireless Communication Systems*, 1(1), 28–35.
25. S. Poornimadarshini, “An Energy-Efficient Edge–AI Framework for Real-Time IoT Analytics in Smart Communication Networks”, *Electronics Communications, and Computing Summit*, vol. 3, no. 4, pp. 1–9, Dec. 2025.