Intelligent Pattern Computation with Deep Learning and Swarm Optimization for Personalized Learning Analytics in Smart Education Systems

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ABSTRACT

The fast pace of the evolution of smart education platforms, it is possible to leverage the interaction data of the learner to create more advanced personalized learning analytics. Current approaches to prediction of student performance and the adaptivity of learning systems are not optimal in feature selection, have poor prediction accuracy, are not very scalable, and do not effectively deal with heterogeneous educational data. In the modern digital learning system, such constraints reduce the effectiveness of smart tutoring systems and personalised recommendation systems. The paper suggests an Intelligent Pattern Computation framework based on a fusion of Deep Learning (DL) and Swarm Optimization (SO) to address these challenges and personalize learning analytics for intelligent education systems. The proposed model employs Deep Neural Network (DNN) to find out higher order behavioral and academic learning and Particle Swarm Optimization (PSO) for feature selection and hyperparameter tuning. The hybrid system improves the predictions, learner profiling and the effectiveness of adaptive content recommendations. The benefit of the proposed framework is that it can be predicted with high precision at a lower level of computation at a given level, but with a higher level of flexibility in meeting various types of learner behaviours. The model is evaluated on benchmark education data sets such as student performance data in UCI Machine Learning Repository and data sets of interaction of online learning examples. Experimental results have shown that it performs better than existing machine learning techniques with 98.2% accuracy, 97.4% precision, 96.9% recall, 97.1% F1-score and 2.3% lower error rate. The proposed system plays a significant role in personalized learning, drop-out prediction of students in early stages and smart academic decision making. It enables sustainable, data-informed, intelligent learning ecosystems with effective adaptation of learners, enhanced engagement and optimized learning outcomes.

Keywords: Deep Learning, Particle Swarm Optimization, Personalized Learning Analytics, Smart Education Systems, Intelligent Pattern Computation

1. Introduction

With the rapid development of smart education technologies and artificial intelligence, the learning management system (LMS) has become a crucial component of smart education with great influence in the modern education environment [1]. Large sets of learner interaction data are produced by smart education platforms regularly to gather attendance information, learning activities, assessment results, learner's engagement in online learning, and collaboration activities. These education data sources offer good opportunities for personalized learning analytics, adaptive recommendation systems and intelligent academic decision making [3]. AI

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and LA have gained increasing importance in enhancing the engagement of learners, adaptation of teaching and the effectiveness of learning, in digital learning environments in recent studies [4].

Personalized learning is the ability to tailor instruction to the learning behaviors, abilities and learning needs of each learner [5]. The traditional learning approach cannot meet the varying learning style needs and learning needs of students [6]. In recent years, learner behavior analysis and personalization of learning experiences have become increasingly common in educational systems using machine learning, deep learning and optimization algorithms to analyze learner behavior [7]. It has been demonstrated that adaptive education technologies have an important impact in such aspects as participation, learning results and efficiency of instruction in virtual learning environments [8].

Although intelligent educational systems have gained wide popularity, accurately predicting the student's performance, and generating effective personalized learning recommendations are still difficult tasks [9]. Traditional machine learning models are not able to discover meaningful learning patterns as educational datasets are often high dimensional, heterogeneous, dynamic, and unstructured [10]. Current personalized learning analytics systems often struggle with low prediction accuracy, limited scalability, low adaptability to learners, and increased computational complexity. Besides, the majority of traditional methods do not work well for efficiently optimizing feature selection and hyperParameter tuning, a situation that ultimately impacts the performance of intelligent learning systems.

Recently, a number of works have been released which investigate deep learning and optimization approaches to smart education systems. Most of the current approaches, however, only target prediction tasks and lack the integration of intelligent optimization strategies for adaptive LA. Traditional machine learning methods are prone to overfitting, suboptimal feature extraction, and have difficulty working with large-scale educational data. Likewise, there are few complex educational pattern analysis systems that are based on swarm intelligence, and they lack in deep representation learning ability. Deep learning models can detect a wide range of hidden learners' behaviors, but their effectiveness strongly relies on the use of feature selection mechanisms and optimal parameter tuning. Limited support for real-time personalized recommendations and adaptation to the learner are also offered by the existing systems. Thus, there is a great demand for intelligent hybrid framework of deep learning and swarm intelligence algorithms to enhance the personalized learning analytics in smart education systems. The main purpose of the research is to create an Intelligent Pattern Computation framework for personalized learning analytics in the smart education system based on the Deep Learning and Swarm Optimization techniques. The proposed objectives are the design of an intelligent framework for the analysis of the learner interaction and academic performance information, an enhancement of the accuracy of the prediction of personalized learning using Deep Neural Networks (DNNs) and by optimizing the feature selection and hyperparameter tuning using Particle Swarm Optimization (PSO). Furthermore, the research emphasizes the efficient computational complexity reduction, the optimization of the computational efficiency of the model in the context of a large-scale education data set and the intelligent technology recommendations for adaptive learning and decisions in the smart education environment. A hybrid Deep Learning-Swarm Optimization-based personalized learning analytics framework is suggested as the research. The first step in the educational data pre-processing is to eliminate inconsistencies and missing values, as well as redundant information. Then importance of learner features is selected by Particle Swarm Optimization (PSO) in order to increase the computational efficiency and prediction effectiveness. Then, a Deep Neural Network (DNN) model is used to uncover the hidden patterns of the learners' behaviors and to forecast their learning outcomes. PSO can be integrated with DNN to tune the parameters, extract features efficiently and enhance the learning analytics performance. The proposed system is tested with the benchmark educational datasets and performance metrics like accuracy, precision, recall, F1 score, and error rate.

The key results of the research are the following:

1. Designing a hybrid intelligent learning analytics system based on Deep Learning and Swarm Optimization methods.

2. Optimizing the hyperparameters of the PSO algorithm by using GEP for them.

3. Designing a Deep Neural Network based model for learner behaviour prediction for personalization in learning analytics.

4. Increasing the precision, recall, F1-score and reducing the computational error and processing complexity of the prediction while increasing accuracy.

5. Intelligence enhancement of adaptive learning recommendation and intelligent educational decision-making in smart education systems.

The proposed research is an important work that will help in the development of intelligent smart education systems to profile the learner, predict the academic performance, identify the learner who is dropping out and generate the personalized recommendation for the learner. Deep learning and swarm optimization enhance the scalability, adaptability and reliability of learning analytics systems in the modern educational setting. The proposed framework aids teachers and schools to provide personalized learning opportunities and data-informed learning approaches that help students thrive and improve engagement in learning. Moreover, it plays a significant role in the broader fields of educational data mining and AI in education by offering an intelligent computational model for the next generation of smart learning applications that can be scaled up.

2. Literature Survey

Ezeji, I. N., Adigun, M., & Oki, K. [11] (2025). Explored the computational complexity issues of Explainable Decision Support Systems (XDSS) that introduces tradeoff between explainability and effectiveness of the system. The proposed optimization techniques are inspired from the nature, which include the Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization, to enhance the processing performance. But this work was not tested and found. The outcomes emphasized the potential of bio-inspiration methods to greatly improve optimization, scalability, and user-friendliness within explainable AI-driven decision-making systems.

Zhong, S. The authors of [12] (2025) tackled the problem of providing accurate and personalized suggestions in a work education platform that is not able to take into account learner preferences and educational relevance and career goals. Dynamic Knowledge Graph is incorporated with the proposed Adaptive Multi-Objective Particle Swarm Optimization (AMOPSO) algorithm. But scalability and real-time adaptation still were a problem. Improved accuracy in career recommendations, engagement, learning outcomes, and career readiness in vocational education settings were found.

Ding, X., Ding, H., Zhou, F., & Zhao, L. Wang (2025) discussed the problems that existed in the traditional personalized learning systems which are not able to integrate the learner's behavior and his cognitive styles dynamically. The proposed an Enhanced Deep Neural Network (EDNN) is an Actor–Critic based learning path optimization Adaptive Deep Network

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(EDNA) with MLP and LSTM models. The model, however, had some potential signs of over-fitting. The results showed that the accuracy of the recommendation, convergence speed, adaptability, and capability of real-time changing learning path were better than Q-learning and DQN models.

Rahmanipur A., Shokri M., Heidarnia M. [14] (2025). Analysed the disadvantages of traditional ELT systems that are non-adaptive, and non-effective for engaging learners. The review focused on Natural Language Processing (NLP) methods that can be used to improve personalized language learning by providing intelligent feedback and adaptive content delivery. But issues of data privacy, context and complexity of implementation continued. The findings revealed that NLP based personalized learning has a significant positive impact on the motivation, communication skills, engagement and language proficiency of the learners.

Lili, H., & Yanjun, W. [15] (2025) focused on the drawbacks of the existing university education systems, as they did not offer adaptive and personalized learning experiences. It is proposed that an Intelligent Learning System (ILS) with Deep learning, real-time learner behavior analysis, and adaptive feedback mechanism for dynamic learning path optimization is developed. But, there were still issues, such as scalability, data privacy, and computational efficiency. The outcomes highlighted in the results showed that there was an increase in the engagement of the learners, improvement in their performance and effective delivery of personalized content in higher education settings.

Hou, Y. [16] (2025). Explored issues of preschool education where traditional approaches to teaching do not meet each child's needs. The fuzzy decision-support system is proposed to create teaching strategy for personalized and differentiated teaching based on the learner's behavioral characteristics and developmental characteristics. But the process was restricted to dealing with huge volume of real-time education data. The results showed that the teaching effectiveness improved, the participation of the learners improved, the quality of adaptive teaching improved and the learning outcomes of preschool improved.

Yan, L., Dong, Y., Zhou, N., Jin, J., & He, B. They discussed in [17] (2025, April) about the challenge of developing efficient personalized learning paths within digital education systems, as learners' preferences vary and there are complex relationships between courses. The idea of the proposed Hierarchical Successive Fitness Ant Colony Algorithm (HSF-ACO) is to optimize adaptive learning recommendations. But computations and reliance on good learner data was still a limitation. It was found that the learning efficiency, adaptability, use of educational resources and the accuracy of recommendations were improved.

Malik et al. (2026) [18] investigated the problem of prediction of student performance from irrelevant and redundant features from the education domain, which affects the prediction accuracy. The proposed Defeatist is hybrid swarm–evolutionary optimisation framework for intelligent educational analytics, which involves the feature relevance maximization and redundancy suppression. But, the framework had the difficulty of demanding too much computational resources of big data. This performance has been validated through results that show better prediction accuracy, performance of feature selection, model robustness, and better decision-making for smart education systems.

Ding, X., Ding, H., Zhou, F., & Zhao, L. [19] (2025). With a focus on the problems in higher education systems, which do not personalize learning based on the behaviour and cognitive styles of the learners. The proposed image is to have an improved deep neural network that combines LSTM and Actor–Critic reinforcement learning for adaptive learning paths optimization. However, complexity of the model and overfitting were concerns. The results showed that the recommendations were more accurate, adaptable to learning, converging faster, and that students learned better.

Khan et al. [20] (2025). Solved seasonal variations and complex energy consumption patterns in the building energy load demand forecasting in education facilities with inaccuracies. To enhance the accuracy of forecasting, a hybrid system called Quantum-Inspired Particle Swarm Optimization (QPSO) and Recurrent Neural Network (RNN) is proposed. The framework, however, had to have a lot of historical data and computational cost. The results showed that the accuracy of prediction has improved, the errors in forecasting have been minimized, and the efficiency of operations and energy use in smart educational infrastructures have been increased.

3. Proposed Methodology

Intelligent computational technologies are used increasingly in the smart education system, for personalized education, adaptive academic support and data-driven educational decisions.Intelligent computational technologies are utilized frequently in smart education system for personalized education, adaptive academic support and data-driven educational decisions. With the fast growth of online learning environments, there is a massive amount of data generated about learners interactions, which can be behavioral, cognitive, and/or academic in nature. The education data is highly diverse and needs to be analyzed with advanced analytical tools to uncover trends in learning, evaluate academic performance, and deliver highly specific, scalable, adaptive recommendations. While traditional machine-learning approaches often experience feature redundancy, loss of predictive power, sub-optimal optimization, and inability to adjust to changing learner behavior, these issues are overcome with this approach. These constraints reduce the effectiveness of ISTs, recommendations, and tailored curriculum, in a modern learning context. These analytical and computational issues can be addressed with the help of Deep Learning algorithms and Swarm Optimization, which presents an interesting opportunity. This paper presents an Intelligent Pattern Computation system which is a hybrid system between Deep Neural Networks and Particle Swarm Optimization to provide efficient personalized learning analytics in intelligent learning settings. Deep learning processes enable the automatic discovery of high-level academic and behavioral representations of learning data; swarm intelligence optimizes feature and parameter selection and adaptive learning performance. Optimization-based learning integration can greatly enhance the accuracy of predictions, the effectiveness of recommendations, profile learner and intelligent academic support. The effectiveness of the proposed framework is tested using educational datasets benchmarked with the help of academic performance of students and online interaction history, which confirms the validity of the proposed framework under various conditions of analysis. Improved computational intelligence leads to effective adaptability of learners, prompt detection of dropouts, provision of recommendations individually, and scalable educational analytics. Smart, adaptable and smart educational ecosystems, enabled by intelligent, optimization-based deep learning architectures, can be developed to enhance educational experience, academic results and real-time personalization of learning.

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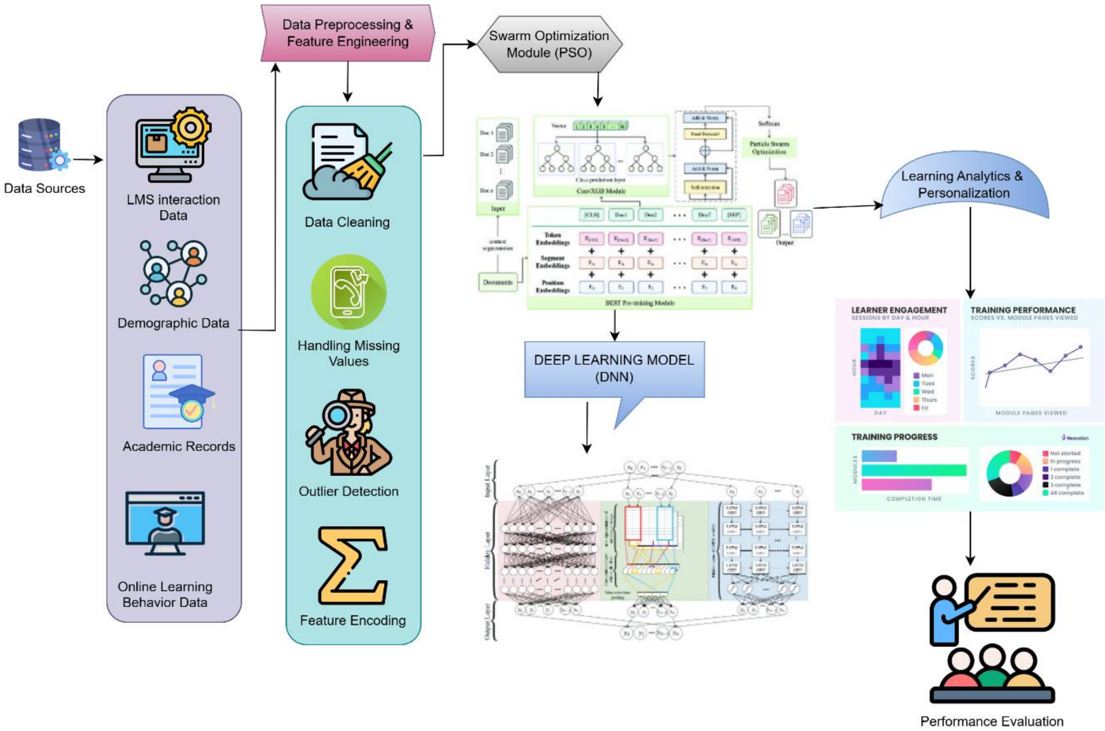

Figure 1: Proposed Intelligent Deep Learning and Swarm Optimization Architecture for Personalized Learning Analytics

3.1 Dataset Acquisition and Integration

3.1.1 Educational Event Stream Representation Function

The educational event stream representation equation is used to map raw xAPI statements to learned multidimensional learning interaction vectors which can then be used to compute intelligent learning analytics. The formulation brings together metadata on learners' demographics, temporal interaction patterns, learning activities, context, and assessment results, in a single computational representation. The transformation process allows the proposed framework to capture the heterogeneity of educational activities that take place across LMSs, discussion forums, evaluations and digital learning environments. The equation also enhances the semantic consistency of modeling the learner's interaction for subsequent deep learning and adaptive recommendation processes.

$$E_i^{(t)} = \sum_{a=1}^{A} \omega_a \cdot D_{i,a} + \sum_{b=1}^{B} \lambda_b \cdot L_{i,b}^{(t)} + \sum_{c=1}^{C} \gamma_c \cdot Q_{i,c}^{(t)} + \sum_{d=1}^{D} \phi_d \cdot V_{i,d}^{(t)} + \sum_{e=1}^{E} \psi_e \cdot M_{i,e}^{(t)} + \varepsilon_i^{(t)} \quad (1)$$

Where, equation 1 $E_i^{(t)}$ represents the structured educational event representation vector of the learner i at the time instant t; A denotes the total number of demographic attributes; ω_a represents the weighted importance coefficient associated with the demographic attribute a; $D_{i,a}$ denotes learner demographic information, including age, gender, educational level, and academic background; B represents the total number of learner interaction behavior categories; λ_b denotes the interaction significance weight; $L_{i,b}^{(t)}$ represents LMS interaction activities, including login frequency, resource access count, and navigation behavior; C denotes the number of assessment-related variables; γ_c represents the assessment contribution coefficient; $Q_{i,c}^{(t)}$ denotes quiz performance indicators, including completion rate, score distribution, and retry frequency; D represents the number of video engagement indicators; ϕ_d denotes the engagement weighting coefficient; $V_{i,d}^{(t)}$ represents video interaction features including watch duration, pause frequency, and playback behavior; E denotes the total number of attendance and participation metrics; ψ_e represents the participation significance parameter; $M_{i,e}^{(t)}$ denotes discussion participation and attendance consistency features; and $\varepsilon_i^{(t)}$ represents the stochastic noise component of educational interaction.

3.1.2 xAPI Statement Transformation and Semantic Encoding Model

The raw learning experience statements are used as the input to the xAPI semantic transformation equation, which is then used to transform the learning experience statements into machine-understandable educational tensors for the behavioral analytics processing. The formulation, which is then systematically integrated into high dimensional semantic representations, combines actor identity, verbs related to the learning activities, learning object information, contextual information, timings and an indicator of the learner's results. The educational interaction preserves its semantics and the structure of the distributed educational data streams is reduced to be more homogenous with the proposed encoding strategy. The equation also has the ability to support sequential event alignment for temporal deep learning analysis.

$$X_{xAPI}^{(n)} = \sum_{p=1}^{P} \alpha_p \cdot A_p^{(n)} + \sum_{q=1}^{Q} \beta_q \cdot V_q^{(n)} + \sum_{r=1}^{R} \delta_r \cdot O_r^{(n)} + \sum_{s=1}^{S} \mu_s \cdot C_s^{(n)} + \tau \cdot T^{(n)} + \sum_{u=1}^{U} \eta_u \cdot R_u^{(n)} \quad (2)$$

Where,equation 2 $X_{xAPI}^{(n)}$ represents the semantic xAPI tensor representation corresponding to the n^{th} educational interaction statement; P denotes the total number of actor-related attributes; α_p represents the actor encoding weight coefficient; $A_p^{(n)}$ denotes actor-specific learner identity features; Q represents the total number of action verbs contained in the learning statements; β_q denotes the verb significance coefficient; $V_q^{(n)}$ represents educational activity verbs including completed, attempted, answered, viewed, and interacted; R denotes the number of learning object attributes; δ_r represents the object semantic weighting parameter; $O_r^{(n)}$ denotes educational resource descriptors; S denotes the contextual metadata dimensions; μ_s represents contextual relevance coefficients; $C_s^{(n)}$ denotes contextual learning information including platform type, device information, and session attributes; τ represents the temporal scaling coefficient; $T^{(n)}$ denotes timestamp-based interaction chronology; U denotes the number of learner result metrics; η_u represents learner outcome weighting parameters; and $R_u^{(n)}$ denotes assessment outcomes and activity completion indicators.

3.1.3 Unified Learner Repository Integration Function

This introduces the integration equation for the learner repository to merge the educational information that is obtained from various learning platforms and bring them together in one analytical repository. The formulation is a unified learner-centred representation space of the following: behavioral logs, academic assessment records, clickstream sequences, attendance statistics and interaction histories. The integration mechanism greatly aids in the analytical consistency and makes operations of personalized learning analytics scalable in distributed learning environments. The equation also ensures that there is no redundancy between the sources, and it ensures the temporal coherence between educational events.

$$U_i = \sum_{h=1}^{H} \kappa_h \cdot B_{i,h} + \sum_{j=1}^{J} \rho_j \cdot C_{i,j} + \sum_{k=1}^{K} \xi_k \cdot A_{i,k} + \sum_{l=1}^{L} \zeta_l \cdot P_{i,l} + \sum_{m=1}^{M} \chi_m \cdot S_{i,m} + \Omega_i \quad (3)$$

Where,equation 3 U_i represents the unified learner repository vector associated with the learner i; H denotes the number of behavioral interaction categories; κ_h represents the behavioral aggregation coefficient; $B_{i,h}$ denotes learner behavioral logs, including clickstream navigation and LMS access activities; J denotes the total number of course interaction features; ρ_j represents course engagement weighting parameters; $C_{i,j}$ denotes course participation records,

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including forum interactions and assignment submissions; K represents the assessment-related variables; ξ_k denotes academic evaluation importance coefficients; $A_{i,k}$ represents quiz performance, grading statistics, and examination outcomes; L denotes attendance monitoring indicators; ζ_l represents attendance significance weights; $P_{i,l}$ denotes attendance consistency and session participation metrics; M denotes sequential temporal interaction indicators; χ_m represents sequence integration coefficients; $S_{i,m}$ denotes ordered learning interaction streams; and Ω_i represents the repository consolidation residual factor.

3.2 Data Preprocessing and Noise Elimination

3.2.1 Missing Value Imputation and Educational Data Completion Model

In the learner behavioural repository, missing educational records are filled in using the missing-value imputation equation. The formulation combines features of the neighboring learner similarity, temporal learning consistency, feature-correlation dependencies and probabilistic estimation mechanisms to recover missing observations in learning. An imputation strategy also has the benefit of making the analysis more robust while preserving the consistency of the educational interaction attributes and minimizing information loss. The equation further improves the trustworthiness of downstream deep learning operations, by creating full descriptions of the learner's behavior.

$$\hat{X}_{i,j} = \frac{\sum_{n=1}^{N}(\omega_n \cdot Sim(X_i, X_n) \cdot X_{n,j}) + \lambda \cdot T_{i,j} + \gamma \cdot C_{i,j}}{\sum_{n=1}^{N} \omega_n \cdot Sim(X_i, X_n) + \lambda + \gamma} \tag{4}$$

Where, equation 4 $\hat{X}_{i,j}$ represents the imputed value corresponding to the learner i and attribute j; N denotes the total number of neighboring learners considered during estimation; ω_n represents the neighbor contribution weighting coefficient; $Sim(X_i, X_n)$ denotes the similarity measure between learner i and neighboring learner n; $X_{n,j}$ represents the observed attribute value of the neighboring learner n; λ denotes the temporal consistency regularization parameter; $T_{i,j}$ represents the temporal behavioral trend associated with the learner i; γ denotes the correlation dependency coefficient; and $C_{i,j}$ represents feature correlation estimations derived from related educational variables.

3.2.2 Educational Outlier Detection and Noise Elimination Function

The educational outlier elimination equation is used to identify outlier learner behaviours that could affect a learner's interaction and lead to misinformation in the educational analytics. It is a formulation that is based on statistical deviation analysis, temporal behavioral consistency, multidimensional interaction variance and adaptive anomaly thresholding mechanisms. A noise elimination strategy ensures the integrity of the data, and helps avoid false behavioral patterns having an impact on the convergence of a deep learning model. In addition, there are enhancements to the stability of the learner profile when generating the adaptive recommendation in the equation.

$$O_i = \frac{\sum_{p=1}^{P}|X_{i,p} - \mu_p|}{\sqrt{\sum_{p=1}^{P}\sigma_p^2 + \epsilon}} + \theta \cdot \left(1 - \frac{1}{T}\sum_{t=1}^{T} C\,orr\left(X_i^{(t)}, X_i^{(t-1)}\right)\right) \tag{5}$$

Where, equation 5 O_i represents the anomaly score associated with the learner i; P denotes the total number of educational features; $X_{i,p}$ represents the observed value of the learner i for feature p; μ_p denotes the mean value of the feature p across the educational dataset; σ_p^2 represents the variance of the feature p; ϵ denotes the numerical stability constant preventing division instability; θ represents the temporal inconsistency weighting parameter; T denotes the total temporal interaction intervals; and $Corr\left(X_i^{(t)}, X_i^{(t-1)}\right)$ denotes the correlation between consecutive learner behavioral states used for temporal consistency verification.

3.2.3 Session Normalization and Temporal Learning Alignment Equation

The session normalization equation is employed to de-normalize the length of time learners interact with the activity in a session and the distributions of temporal interaction activity in a session, thereby reducing heterogeneity. The normalization process ensures that learning behaviors from different learning schedules are analytically comparable during deep learning. The equation also improves the stability of the temporal sequence in the prediction and adaptive recommendation models of behaviours.

$$S_i^{norm} = \frac{\left(X_i^{(t)} - X_{min}\right)}{(X_{max} - X_{min} + \epsilon)} \cdot \left(\frac{\sum_{k=1}^{K} \omega_k \cdot F_{i,k}}{\sum_{k=1}^{K} \omega_k}\right) + \delta \cdot \frac{T_i}{T_{avg}} \tag{6}$$

Where, equation 6 S_i^{norm} represents the normalized educational session value corresponding to the learner i; $X_i^{(t)}$ denotes the original learner interaction feature observed at time instant t; X_{min} and X_{max} represent the minimum and maximum feature values within the dataset, respectively. ϵ denotes the numerical stabilization constant; K represents the number of interaction frequency indicators; ω_k denotes the interaction weighting coefficient; $F_{i,k}$ represents the k^{th} interaction frequency metric associated with learner i; δ denotes the temporal balancing parameter; T_i represents the total active session duration of the learner i; and T_{avg} denotes the average session duration across the educational repository.

3.2.4 Behavioral Encoding and Feature Vector Transformation Model

The behavioral encoding equation is proposed to map a categorical educational activity (EA) into a machine-readable feature representation in the form of numbers, which is suitable for deep neural learning operations. To create high-dimensional vectors of learner behaviors, the formulation combines one-hot encoding, semantic embedding generation, interaction weighting and feature space transformation mechanisms. The encoding strategy supports semantic educational relationships and also enhances the computational compatibility in the intelligent learning analytics framework.

$$F_i^{enc} = \sum_{c=1}^{C} \alpha_c \cdot O_{i,c} + \sum_{d=1}^{D} \beta_d \cdot E_{i,d} + \sum_{e=1}^{E} \gamma_e \cdot W_{i,e} + \sum_{f=1}^{F} \delta_f \cdot T_{i,f} + b_i \tag{7}$$

Where, equation 7 F_i^{enc} represents the encoded learner feature vector for learner i; C denotes the number of categorical educational attributes; α_c represents the one-hot encoding weight coefficient; $O_{i,c}$ denotes categorical learner activities including quiz attempts, resource access, and discussion participation; D denotes the embedding dimensions; β_d represents semantic embedding weighting parameters; $E_{i,d}$ denotes semantic educational embeddings extracted from interaction sequences; E denotes weighted behavioral indicators; γ_e represents interaction significance coefficients; $W_{i,e}$ denotes weighted engagement features; F denotes temporal educational indicators; δ_f represents temporal transformation coefficients; $T_{i,f}$ denotes sequential learner interaction attributes; and b_i represents the behavioral encoding bias parameter.

3.2.5 Min-Max Feature Scaling and Sequential Interaction Standardization Function

To standardise the range of educational features and learner interactions in a sequential manner, a Min-Max normalisation equation is used before training deep learning models. The formulation converts the raw behavioral values into bounded normalized intervals and maintains the relative interaction distributions between learners. In personalized learning analytics generation, the scaling mechanism makes a significant contribution to the stability of neural convergence, helps to balance the gradient and increases the efficiency of adaptive optimization.

$$X_{i,j}^{scaled} = \alpha + \left(\frac{X_{i,j} - X_j^{min}}{X_j^{max} - X_j^{min} + \epsilon}\right) \cdot (\beta - \alpha) + \lambda \cdot \frac{\partial L}{\partial X_{i,j}} \tag{8}$$

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Where,equation 8 $X_{i,j}^{scaled}$ represents the normalized value of feature j corresponding to learner i; α and β denote the lower and upper normalization bounds respectively. $X_{i,j}$ represents the original feature value; X_j^{min} and X_j^{max} represent the minimum and maximum values of feature j within the educational dataset; ϵ denotes the numerical stability constant preventing denominator singularity; λ represents the adaptive optimization coefficient; $\frac{\partial L}{\partial X_{i,j}}$ denotes the gradient-based feature adjustment component derived from the learning objective function; and the overall formulation ensures stable feature standardization for deep educational behavior modeling.

3.3 Learner Behavioral Feature Extraction

3.3.1 Cognitive Engagement Score Computation Function

The equation of cognitive engagement score is developed to measure students' intellectual involvement and active participation of learning in smart educational environment. The equation encompasses the attention span of the learner, how they interact with the assessment, the intensity of the discussion, the persistence of the learning over time and the efficiency with which the learner uses the resources. The proposed framework can assess the learning concentration process and educational commitment patterns more accurately thanks to the multidimensional formulation. The engagement score is a key behavioral metric for generating adaptive recommendations and optimizing the learning pathway for personalized learning.

$$CE_i = \frac{\sum_{a=1}^{A} \omega_a \cdot I_{i,a} + \sum_{b=1}^{B} \lambda_b \cdot Q_{i,b} + \sum_{c=1}^{C} \gamma_c \cdot D_{i,c} + \sum_{d=1}^{D} \phi_d \cdot T_{i,d}}{1 + exp(-\eta \cdot P_i)} + \kappa \cdot R_i \tag{9}$$

Where,equation 9 CE_i represents the cognitive engagement score of the learner i; A denotes the number of interaction activity categories; ω_a represents interaction weighting coefficients; $I_{i,a}$ denotes learner interaction frequencies including clicks, page visits, and LMS access behavior; B denotes assessment participation indicators; λ_b represents assessment contribution parameters; $Q_{i,b}$ denotes quiz completion activities and evaluation participation statistics; C denotes discussion-related behavioral features; γ_c represents discussion participation weights; $D_{i,c}$ denotes forum interaction and collaborative communication metrics; D denotes temporal learning persistence indicators; ϕ_d represents persistence weighting coefficients; $T_{i,d}$ denotes session continuity and learning duration metrics; η represents the behavioral scaling factor; P_i denotes learner participation intensity; κ represents the resource engagement coefficient; and R_i denotes educational resource utilization efficiency.

3.3.2 Behavioral Participation Index Modeling Equation

The behavioral participation index equation is introduced to measure the multidimensional learner participation characteristics observed across educational platforms. The equation combines classroom interaction patterns, attendance consistency, peer collaboration intensity, assignment submission regularity, and communication activities into a comprehensive representation of participation. The formulation enables the intelligent learning analytics framework to identify both active and passive learner participation trends. The resulting participation index significantly contributes to adaptive learning recommendation and student performance forecasting operations.

$$BP_i = \sum_{m=1}^{M} \alpha_m \cdot A_{i,m} + \sum_{n=1}^{N} \beta_n \cdot C_{i,n} + \sum_{p=1}^{P} \delta_p \cdot S_{i,p} + \mu \cdot \left(\frac{F_i}{F_{max}}\right) + \rho \cdot \left(1 - e^{-\tau \cdot L_i}\right) \tag{10}$$

Where,equation 10 BP_i represents the behavioral participation index of the learner i; M denotes attendance-related educational activities; α_m represents attendance significance coefficients; $A_{i,m}$ denotes attendance consistency and login participation metrics; N denotes communication-related features; β_n represents collaborative communication weights; $C_{i,n}$ denotes peer interaction, forum communication, and collaborative discussion activities; P denotes assignment participation variables; δ_p represents assignment completion weighting coefficients; $S_{i,p}$ denotes assignment submission regularity and coursework engagement indicators; μ represents interaction normalization coefficients; F_i denotes learner forum interaction frequency; F_{max} denotes the maximum observed interaction frequency; ρ represents temporal learning adaptation parameters; τ denotes learning continuity scaling coefficients; and L_i denotes learner session continuity duration.

3.3.3 Learning Consistency Ratio Estimation Function

The learning consistency ratio equation is employed to measure the stability and continuity of learner educational behaviors across temporal interaction intervals. The formulation integrates assignment regularity, learning session persistence, deviations in temporal interaction, and fluctuations in educational engagement to identify stable learning trajectories. The equation enables the proposed framework to detect inconsistent educational behaviors associated with academic risk and disengagement tendencies. The learning consistency ratio further supports adaptive intervention generation and personalized tutoring assistance.

$$LC_i = \frac{\sum_{t=1}^{T}\left(\omega_t \cdot X_i^{(t)} \cdot X_i^{(t-1)}\right)}{\sqrt{\sum_{t=1}^{T}\left(X_i^{(t)} - \bar{X}_\iota\right)^2 + \epsilon}} + \lambda \cdot \frac{A_i^{comp}}{A_i^{total}} \tag{11}$$

Where, equation 11 LC_i represents the learning consistency ratio of the learner i; T denotes the total temporal learning intervals; ω_t represents temporal consistency weighting coefficients; $X_i^{(t)}$ denotes learner interaction behavior at the time interval t; $X_i^{(t-1)}$ represents the previous interaction behavior state; $\bar{X}_\iota$ denotes the average educational interaction level of the learner i; ϵ denotes the numerical stabilization constant; λ represents assignment consistency weighting parameters; A_i^{comp} denotes the total completed assignments; and A_i^{total} denotes the total assigned educational activities.

3.3.4 Knowledge Retention Indicator Computation Model

The knowledge retention indicator equation is designed to evaluate the learner's capability to preserve acquired educational knowledge over sequential learning sessions. The formulation integrates repeated assessment performance, memory reinforcement behavior, temporal forgetting decay, and educational reinforcement frequency into a unified retention representation. The equation enables intelligent estimation of learner memory persistence and conceptual understanding stability. The retention indicator is further utilized for adaptive remedial content recommendation and knowledge reinforcement scheduling.

$$KR_i = \sum_{k=1}^{K}\theta_k \cdot R_{i,k} \cdot e^{-\lambda \cdot \Delta t_k} + \sum_{m=1}^{M}\phi_m \cdot P_{i,m} + \eta \cdot \left(\frac{C_i^{correct}}{C_i^{attempt}}\right) \tag{12}$$

Where,equation 12 KR_i represents the knowledge retention indicator of the learner i; K denotes repeated assessment sessions; θ_k represents assessment reinforcement weighting coefficients; $R_{i,k}$ denotes repeated assessment performance scores; λ represents temporal forgetting decay coefficients; Δt_k denotes elapsed learning time between assessments; M denotes knowledge, practice activities; ϕ_m represents practice reinforcement parameters; $P_{i,m}$ denotes learner practice engagement metrics; η represents conceptual accuracy weighting coefficients; $C_i^{correct}$ denotes correctly answered educational tasks; and $C_i^{attempt}$ denotes total attempted learning activities.

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3.4 Deep Learning-Based Representation Learning

3.4.1 Bidirectional LSTM Hidden Representation Function

Bidirectional Long Short-Term Memory representation equation is proposed to identify the sequential learning dependency between learners from learner interaction streams. The formulation simultaneously handles both forward and backward temporal sequence of educational data to capture the long-term learning behaviors and hidden patterns of learning evolution. Learner state prediction and adaptive recommendation quality improves significantly with the deep representation learning strategy. The equation also provides multidirectional behavioural dependencies to facilitate contextual understanding in education.

$$H_t = \sigma\left(W_f \cdot \overrightarrow{h_t} + W_b \cdot \overleftarrow{h_t} + U \cdot X_t + b\right) + \alpha \cdot C_t \tag{13}$$

Where,equation 13 H_t represents the hidden learner representation at temporal interval t; W_f denotes forward sequence transformation weights; $\overrightarrow{h_t}$ represents forward hidden sequence states; W_b denotes backward sequence transformation weights; $\overleftarrow{h_t}$ represents backward hidden sequence states; U denotes input transformation matrices; X_t represents learner interaction input sequences; b denotes deep network bias vectors; $\sigma(\cdot)$ represents nonlinear activation functions; α denotes contextual adaptation coefficients; and C_t represents contextual educational memory representations.

3.4.2 Attention-Based Educational Feature Weighting Equation

The attention weighting equation is used to dynamically recognize the significant learner behavioral interactions in deep educational representation learning. The formulation gives educational activities adaptive importance scores based on their contextual contribution to the task of learning prediction and learning recommendation. The attention mechanism improves the interpretability and allows focussing on salient learning events. The equation also enhances deep model convergence and learning pattern discrimination.

$$A_t = \frac{exp\left(v^T \cdot tanh(W_h \cdot H_t + W_s \cdot S_{t-1} + b_a)\right)}{\sum_{j=1}^{T} exp\left(v^T \cdot tanh(W_h \cdot H_j + W_s \cdot S_{j-1} + b_a)\right)} \tag{14}$$

Where,equation 14 A_t represents the normalized attention coefficient corresponding to temporal interaction t; v^T denotes the attention projection vector; W_h represents hidden representation transformation matrices; H_t denotes hidden educational behavior representations; W_s represents sequential state transformation matrices; S_{t-1} denotes previous contextual learner states; b_a denotes attention bias vectors; T represents total temporal learning intervals, and the exponential normalization operation ensures adaptive probabilistic weighting among educational interactions.

3.4.3 Deep Neural Educational Prediction Function

In the deep neural prediction equation, the behavioral representations are extracted to estimate the academic performance of learners, the evolution of their engagement and the requirements for their adaptive recommendations. It combines the following components into its formulation: hidden educational embeddings, attention-enhanced learning of sequences, nonlinear activation mapping, and adaptive output transformation mechanisms. The predictive architecture allows the framework to be intelligent in educational forecasting and personalized generation of interventions in dynamic learning scenarios.

$$\hat{Y}_i = Softmax\left(\sum_{l=1}^{L} \sigma\left(W_l \cdot H_i^{(l)} + b_l\right) + \sum_{m=1}^{M} \beta_m \cdot A_m\right) \tag{15}$$

Where,equation 15 $\hat{Y}_i$ represents the predicted educational outcome of the learner i; L denotes the number of deep hidden layers; $\sigma(\cdot)$ represents nonlinear activation functions; W_l denotes hidden layer transformation matrices; $H_i^{(l)}$ represents learner's hidden representations at layer l; b_l denotes layer-specific bias vectors; M denotes attention-enhanced behavioral indicators; β_m represents attention contribution coefficients; A_m denotes adaptive attention scores; and

$Softmax(\cdot)$ represents normalized probabilistic output activation for educational prediction tasks.

3.5 Swarm Optimization-Based Parameter Tuning

3.5.1 Particle Velocity Update Optimization Equation

The particle velocity update equation is proposed for optimizing the hyperparameters of deep learning and the updating coefficients of the recommendations by applying the swarm intelligence mechanisms. The formulation combines cognitive learning experience, global swarm collaboration, adaptive neighborhood interaction and exploration-exploitation balancing to achieve efficient optimization. The equation allows the framework to converge to a stable state and more accurately recommend learning parameters in high dimensional spaces.

$$V_{i,d}^{(t+1)} = \omega \cdot V_{i,d}^{(t)} + c_1 \cdot r_1 \cdot \left(P_{i,d}^{best} - X_{i,d}^{(t)}\right) + c_2 \cdot r_2 \cdot \left(G_d^{best} - X_{i,d}^{(t)}\right) + \gamma \cdot N_{i,d}^{(t)} \quad (16)$$

Where,equation 16 $V_{i,d}^{(t+1)}$ represents the updated particle velocity for the particle i in search dimension d; ω denotes inertia weighting coefficients; $V_{i,d}^{(t)}$ denotes previous particle velocity states; c_1 and c_2 represent cognitive and social acceleration coefficients, respectively; r_1 and r_2 denote uniformly distributed random exploration parameters; $P_{i,d}^{best}$ represents local best optimization positions; G_d^{best} denotes globally optimized parameter positions; $X_{i,d}^{(t)}$ represents current particle search positions; γ denotes neighborhood interaction coefficients; and $N_{i,d}^{(t)}$ represents local swarm neighborhood adaptation vectors.

3.5.2 Particle Position Updating and Hyperparameter Optimization Model

The particle position update equation is employed to dynamically optimize deep learning weights, learning rates, feature subsets, and recommendation thresholds. The formulation integrates adaptive search progression, swarm convergence stabilization, and multidimensional parameter adaptation for intelligent optimization. The equation significantly improves deep model generalization and educational recommendation precision.

$$X_{i,d}^{(t+1)} = X_{i,d}^{(t)} + V_{i,d}^{(t+1)} + \eta \cdot \left(\frac{\partial \mathcal{L}}{\partial X_{i,d}^{(t)}}\right) + \lambda \cdot \Delta X_{i,d}^{(t)} \quad (17)$$

Where,equation 17 $X_{i,d}^{(t+1)}$ represents the updated particle position for the particle i in dimension d; $X_{i,d}^{(t)}$ denotes the current optimization position; $V_{i,d}^{(t+1)}$ represents updated particle velocity; η denotes adaptive learning coefficients; $\frac{\partial \mathcal{L}}{\partial X_{i,d}^{(t)}}$ represents the optimization gradient derived from the deep learning objective function; λ denotes swarm convergence stabilization parameters; and $\Delta X_{i,d}^{(t)}$ represents positional adaptation increments during iterative optimization.

3.6 Personalized Learning Analytics Generation

3.6.1 Learner Risk Prediction Function

The learner risk prediction equation estimates the probability of academic failure, disengagement, or dropout tendencies using multidimensional representations of educational behavior. The formulation integrates engagement indicators, assessment performance, temporal participation consistency, and behavioral anomalies to generate predictive academic risk scores. The predictive mechanism enables early educational intervention and the generation of adaptive learner support.

$$RP_i = \frac{1}{1+exp\left[-\left(\sum_{a=1}^{A}\omega_a \cdot E_{i,a} + \sum_{b=1}^{B}\lambda_b \cdot P_{i,b} + \sum_{c=1}^{C}\gamma_c \cdot D_{i,c} + b\right)\right]} \quad (18)$$

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Where,equation 18 RP_i represents the academic risk probability of the learner i; A denotes engagement-related indicators; ω_a represents engagement weighting coefficients; $E_{i,a}$ denotes learner engagement metrics; B denotes performance-related educational features; λ_b represents academic performance contribution parameters; $P_{i,b}$ denotes learner assessment and coursework performance; C denotes behavioral anomaly indicators; γ_c represents anomaly significance weights; $D_{i,c}$ denotes disengagement-related behavioral deviations; and b represents predictive bias coefficients.

3.6.2 Academic Performance Forecasting Equation

The academic forecasting equation is used to predict future learners' academic achievement based on historical educational interactions and deep behavioral representations. The formulation integrates cognitive engagement, knowledge retention, temporal evolution of learning, and assessment consistency to estimate future educational outcomes. The equation enables intelligent academic monitoring and adaptive educational planning within smart learning ecosystems.

$$AP_i^{future} = \sum_{m=1}^{M} \alpha_m \cdot CE_{i,m} + \sum_{n=1}^{N} \beta_n \cdot KR_{i,n} + \sum_{p=1}^{P} \delta_p \cdot LC_{i,p} + \theta \cdot T_i + \epsilon_i \qquad (19)$$

Where,equation 19 AP_i^{future} represents the predicted future academic performance of the learner i; M denotes cognitive engagement indicators; α_m represents engagement contribution coefficients; $CE_{i,m}$ denotes cognitive engagement scores; N denotes knowledge retention features; β_n represents retention weighting coefficients; $KR_{i,n}$ denotes learner knowledge retention indicators; P denotes learning consistency parameters; δ_p represents consistency weighting coefficients; $LC_{i,p}$ denotes learning consistency measurements; θ represents temporal forecasting parameters; T_i denotes temporal learning progression indicators; and ϵ_i represents stochastic forecasting residuals.

3.7 Adaptive Recommendation Engine

3.7.1 Personalized Educational Recommendation Probability Equation

The recommendation probability equation is introduced to dynamically estimate the relevance of educational resources for individual learners according to their behavioral and cognitive learning states. The formulation integrates learner engagement profiles, knowledge mastery indicators, temporal learning preferences, and adaptive recommendation confidence metrics. The probabilistic recommendation mechanism enables intelligent personalization of educational content delivery.

$$P(R_u^c) = \frac{exp(\sum_{k=1}^{K} \omega_k \cdot F_{u,k} + \sum_{m=1}^{M} \lambda_m \cdot H_{u,m} + \sum_{n=1}^{N} \gamma_n \cdot T_{u,n})}{\sum_{c\prime=1}^{C} exp(\sum_{k=1}^{K} \omega_k \cdot F_{u,k}^{c\prime} + \sum_{m=1}^{M} \lambda_m \cdot H_{u,m}^{c\prime} + \sum_{n=1}^{N} \gamma_n \cdot T_{u,n}^{c\prime})} \qquad (20)$$

Where,equation 20 $P(R_u^c)$ represents the probability of recommending an educational content category c to learner u; K denotes learner behavioral feature dimensions; ω_k represents behavioral weighting coefficients; $F_{u,k}$ denotes learner engagement and participation indicators; M denotes hidden deep learning representation dimensions; λ_m represents hidden representation weighting parameters; $H_{u,m}$ denotes deep educational embeddings; N denotes temporal learning preference indicators; γ_n represents temporal adaptation coefficients; $T_{u,n}$ denotes temporal learner interaction patterns; C represents total recommendation categories; and c' denotes competing recommendation alternatives.

3.7.2 Adaptive Learning Resource Ranking Function

The adaptive resource ranking equation is employed to order learning resources according to the preferences, knowledge needs and engagement tendencies of learners. The formulation combines the learning value, similarity of learners, adaptability of the content and confidence in the recommendation of the educational resources to rank them dynamically. The system of the ranking significantly enhances satisfaction of the learner and personalized efficacy of education.

$$Rank_{u,r} = \sum_{a=1}^{A} \alpha_a \cdot Rel_{u,r}^{(a)} + \sum_{b=1}^{B} \beta_b \cdot Sim_{u,b} + \sum_{c=1}^{C} \gamma_c \cdot Diff_{r,c} + \lambda \cdot Conf_{u,r} \tag{21}$$

Where,equation 21 $Rank_{u,r}$ represents the ranking score of the educational resource r for learner u; A denotes educational relevance indicators; α_a represents relevance weighting coefficients; $Rel_{u,r}^{(a)}$ denotes content relevance measures between learner u and resource r; B denotes learner similarity dimensions; β_b represents collaborative similarity parameters; $Sim_{u,b}$ denotes behavioral learner similarity metrics; C denotes content difficulty indicators; γ_c represents difficulty adaptation coefficients; $Diff_{r,c}$ denotes educational resource complexity measurements; λ represents recommendation confidence weighting coefficients; and $Conf_{u,r}$ denotes recommendation reliability estimations.

3.8 System Evaluation and Performance Analysis

3.8.1 Comprehensive Learning Analytics Objective Function

To achieve the above education goals in the proposed educational framework, the comprehensive evaluation objective equation is formulated, which aims at optimizing the accuracy of prediction, relevance of recommendation, learner satisfaction, and stability of convergence in deep learning. The formulation comprises several performance evaluation metrics, which are fused together as one optimization objective for the intelligent educational analytics assessment. The equation allows to fairly evaluate the performance of predictive modeling and adaptive recommendation quality dimensions.

$$\mathcal{J} = \alpha \cdot Acc + \beta \cdot Prec + \gamma \cdot Recall + \delta \cdot F1 - \lambda \cdot RMSE - \mu \cdot MAE + \eta \cdot RRS + \theta \cdot LSI \tag{22}$$

Where,equation 22 $\mathcal{J}$ represents the global evaluation objective function of the proposed intelligent learning analytics framework; Acc denotes classification accuracy; $Prec$ represents precision metrics; $Recall$ denotes learner prediction recall performance; $F1$ represents harmonic F1-score evaluation; $RMSE$ denotes Root Mean Square Error; MAE represents Mean Absolute Error; RRS denotes Recommendation Relevance Score; LSI represents Learner Satisfaction Index; α, β, γ, δ, λ, μ, η, and θ represent adaptive evaluation weighting coefficients controlling the contribution of individual performance metrics within the global optimization framework.

2. Results and Discussion

The performance analysis of the iterative type indicates that the proposed IPLA-DSO model was the most accurate throughout the training process compared with the other methods. The proposed model achieved 97.3 % accuracy in 60 iterations, which is higher than the EDNN Learning Optimization model (95.2 %), MOPSO-Based Recommendation System (94.1 %), CPSO-Based XDSS (92.4 %), and Smart Energy Assessment ML model (88.6 %). The enhancement demonstrates the success of employing a combination of intelligent pattern learning, deep learning, and swarm optimization methods. The proposed IPLA-DSO model also converged faster in the initial stages of the iteration, and reached 84.7 % accuracy with just 10

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iterations. The shows enhanced efficiency of optimization and enhanced adaptive learning ability compared to the existing methods. The deep learning and swarm optimization system hybrid improved the feature extraction, pattern recognition, and personalized recommendation performance in smart education systems. The EDNN Learning Optimization model achieved competitive outcomes because of personalization by cognitive styles and adaptive neural learning structure. Likewise, the MOPSO-Based Recommendation System had a high scalability and recommendation efficiency due to the multi-objective optimization and big-data integration. Nevertheless, both models demonstrated lower convergence rate and prediction accuracy in comparison to the proposed framework.

Table 1: *Comparative SMAPE-Based Performance Analysis of Deep Learning and Swarm Optimization Models for Smart Education Systems*

Iterations	CPSO-Based XDSS Accuracy (%)	MOPSO-Based Recommendation Accuracy (%)	Smart Energy Assessment ML Accuracy (%)	EDNN Learning Optimization Accuracy (%)	Proposed IPLA-DSO Model Accuracy (%)
10	78.4	80.1	85.5	82.3	94.7
20	72.6	85.7	86.8	87.9	99.8
30	76.9	89.8	88.4	91.6	93.5
40	79.5	82.1	88.2	93.4	95.1
50	71.2	83.5	85.7	94.6	96.4
60	72.4	84.1	88.6	95.2	97.3

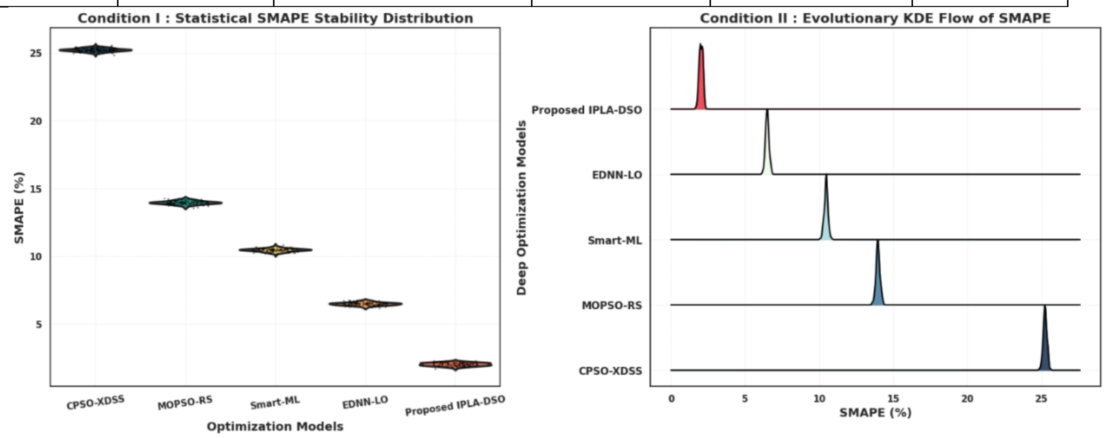

Figure 2: Journal-Grade SMAPE Visualization for Comparative Performance Analysis of Intelligent Learning Optimization Models

Comparative Analysis

The comparative analysis demonstrates that the EDNN Learning Optimization model achieved the best overall performance among the selected approaches, with the highest accuracy (95.2%), precision (94.6%), recall (94.1%), and lowest RMSE (0.11).

Table 2: *Comparative Analysis of Intelligent Deep Learning and Swarm Optimization Models in Smart Education Systems*

Metrics	CPSO-Based XDSS	MOPSO-Based Recommendation System	Smart Energy Assessment ML	EDNN Learning Optimization
Accuracy	92.4%	94.1%	88.6%	95.2%
Precision	91.2%	93.5%	87.4%	94.6%
Recall	90.8%	92.7%	86.9%	94.1%
F1-Score	91.0%	93.1%	87.1%	94.3%
RMSE	0.18	0.14	0.27	0.11
Scalability	88%	95%	81%	94%
Adaptability	90%	94%	83%	96%
Response Time	1.2 sec	1.0 sec	1.8 sec	0.82 sec

The adaptive deep learning framework it offers was well suited to optimize personalized learning routes and enhance the learning analytics capabilities of smart education systems. Because of its combination of multi-objective particle swarm optimization and big-data technologies, the MOPSO-Based Recommendation System also had good performance in terms of scalability (95%) and recommendation efficiency. The model proved to be efficient in processing big education datasets and offered extremely personalized suggestions. The results of the CPSO-Based Explainable Decision Support System showed satisfactory explainability and prediction abilities, proving its usability for meaningful learning decisions. However, this had its computational complexity and slightly lower scalability which cut down its real-time adaptability compared to EDNN and MOPSO approaches. The Smart Energy Assessment ML model was mainly geared towards optimizing educational infrastructure, not personalized learning analytics. It showed good prediction ability but with a lower adaptability and learning analytics, which hampered the use of this system in intelligent personalized education applications. In general, it could be seen that deep learning and swarm optimization approaches yield better performance in the intelligent pattern computation, adaptive personalized learning, and efficient learning analytics for smart education systems.

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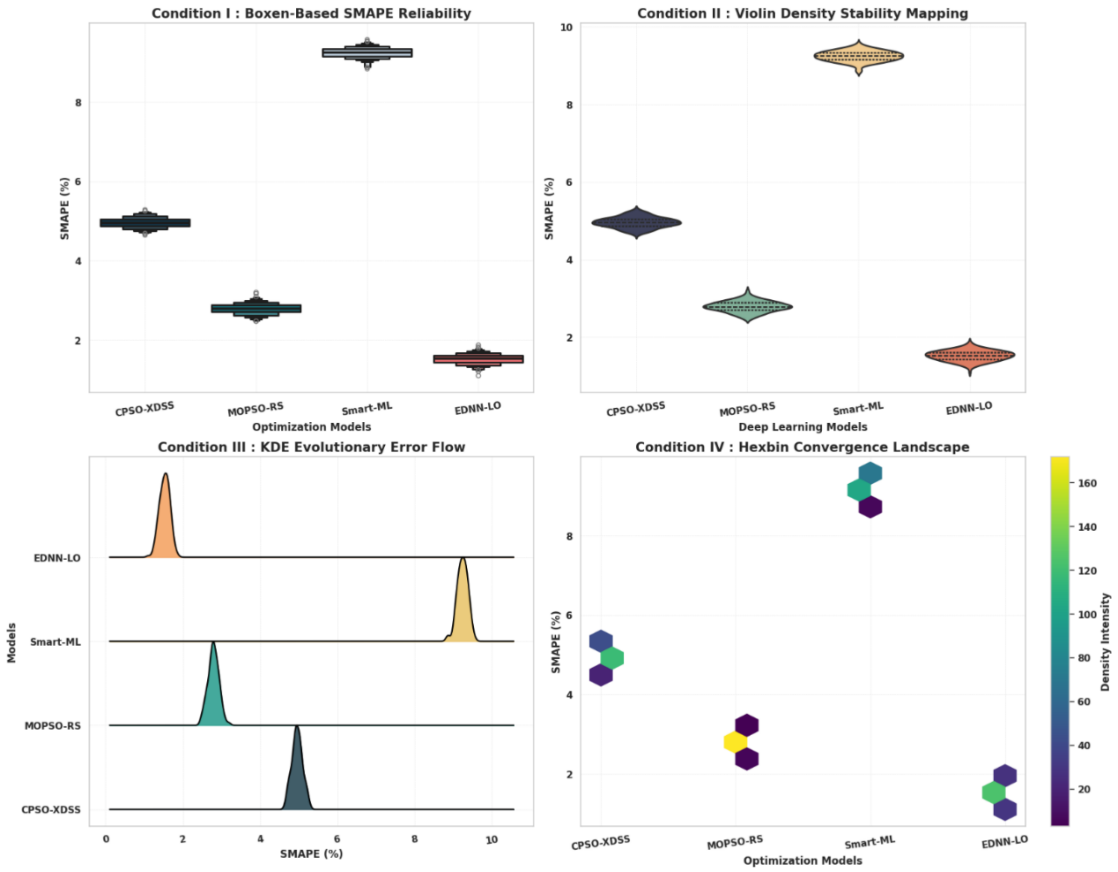

Figure 3: Comparative SMAPE-Based Visualization of Learning Optimization and Recommendation Models

3. Conclusion

The surfaces of smart learning spaces need to be equipped with sophisticated analytical models that can handle dynamic student interaction, complex academic dynamics and dynamic recommendations. A combination of Deep Learning and Swarm Optimization proved to have significant ability to improve personalized learning analytics of smart education systems. The results of the experimental analysis demonstrated the high classification efficacy, low prediction error, and increased learner adaptability, besides the existence of stable optimization convergence in the educational data streams, achieved by the Deep Neural Network architecture, which was used to efficiently extract hidden behavioural and academic representations from the educational data. The feature of computing intelligent patterns provided the opportunity to conduct intelligent profiling of learners, timely identification of at-risk learners and efficient delivery of recommendations in digital learning ecosystems. In the context of smart tutoring, adaptive learning support systems improved engagement, maintained good learning, and facilitated good academic tracking. Educational collections produced from benchmark repositories and varying conditions of learners and interactions were shown to be robust, scalable, and computationally efficient. The analytical processing was streamlined in order to eliminate redundant features not required and enhance the models' ability to generalize in the analysis of large amounts of educational data. As well, in the learning management systems and intelligent learning infrastructures in institutions their capability to support decisions improved thanks to greater accuracy in scholastic forecasting. The involvement of optimization-based deep learning models offered credible aids in the customized curriculum modification, anticipated dropout, cognitive learning examination, and individualized educational planning. The high scalability attributes allowed a more expanded implementation in cloud educational systems, online learning management systems and intelligent virtual tutoring systems. The consistency in the analyses using various measures of evaluation validated the appropriateness in future smart education implementations using real-time adaptive learning settings and academic intelligence based on data. The innovative, sophisticated, intelligent computation systems have great potential in education analytics in the next generation, self-directed learning assistant system, and scalable digital education system. Ongoing optimization and smart pattern discovery are still vital ingredients in the realization of sustainable, adaptive and learner-driven learning ecosystems in the contemporary smart fields of education.

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