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Article

A Hybrid Ensemble Learning and Case-Based Reasoning Framework for Learner Intelligence Prediction and Personalized Adaptive Learning

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Abstract: Due to the growing need for intelligent learning systems that can cater to the different demands of learners, personalized adaptive learning is an essential research topic in educational data mining. Most existing learner prediction models are based on academic achievement and ignore the latent learner traits and tailored recommendation mechanisms. To overcome these constraints, this paper introduces a Hybrid Ensemble Learning and Case-Based Reasoning Framework for Learner Intelligence Prediction and Personalized Adaptive Learning. The proposed system combines Feature Engineering, Principal Component Analysis (PCA), K-Means clustering, Hybrid Ensemble Learning and Case-Based Reasoning (CBR) in one adaptive learning architecture. The learner intelligence is estimated and the learners are classified into five adaptive learning groups using four manufactured learner attributes, Study Habits Score, Academic Participation Score, Academic Performance Score and Learner IQ Score. To examine the robustness and generalization power of the proposed framework in diverse educational contexts two benchmark educational datasets OULAD and xAPI-Edu-Data were used. Experimental findings indicate that the Hybrid Ensemble model obtained 97.92% classification accuracy on the xAPI dataset and still performed well on the OULAD dataset. Furthermore, the CBR module attained an average similarity score of 83.01%, a retrieval accuracy of 99.58%, and a recommendation coverage of 100%, and produced five individualized recommendation methods for distinct learner profiles. Comparative research in both datasets validates the scalability, robustness and efficacy of the proposed framework of learner intelligence prediction and customized adaptive learning. The suggested framework offers an intelligent decision support system that may improve student engagement, educational results, and data-driven adaptive learning environments.
Keywords: Adaptive Learning, Educational Data Mining, Learner Intelligence Prediction, Ensemble Learning, Personalized Learning, Machine Learning.

1. Introduction

The fast development of digital technology has considerably altered the conventional schooling into intelligent and data-driven learning environments, which are capable of providing tailored learning experiences. With the rising popularity of online learning platforms, LMS and intelligent educational technologies, a large amount of educational data has been produced, depicting learners' academic performance, study habits, participation, assessment results, and interaction behaviors. Educational data such as these provide excellent prospects for the development of intelligent learning systems that can assess learners characteristics, recognize learning patterns and promote individualized educational decision-making. Consequently, AI, ML, EDM, and LA have emerged as powerful research domains to develop adaptive learning systems to enhance learners' engagement, academic performance, and overall education effectiveness.

Adaptive learning systems aim to customize instructional information to suit the requirements, capabilities, learning rate, and behavioral traits of the learner. Traditional e-learning systems usually provide the same learning content to all learners. Adaptive learning environments assess data from learners and customize learning content in real time to optimize learning results. State of the art adaptive learning systems have made impressive advances in forecasting learner performance, identifying children at-risk, providing learning materials, and enhancing educational interventions. Nevertheless, most current methods are dedicated to predicting academic achievement using single machine learning models, and they seldom take into account the evaluation of learner intelligence, the hidden features of learners, and the tactics of tailored recommendation. Moreover, many of the present systems are based on narrow student indicators and do not combine numerous analytical methodologies in a single intelligent framework for full learner profiling.

Increasingly, machine learning algorithms are used for educational prediction tasks, since they may reveal hidden links in complicated educational datasets. Some classification algorithms have been effectively used for learner performance prediction, dropout detection and academic accomplishment monitoring. These algorithms provide good prediction accuracy. However, single-model methods have limited generalization capacity and less resilience in varied educational contexts. Recent breakthroughs in ensemble learning have shown the power of using the complementarity of diverse machine learning algorithms to increase the prediction accuracy, stability and dependability of the ensemble classifier. In addition to predictive modeling, EDM and LA provide sophisticated analytical approaches for deriving relevant educational information from student data. Researchers may use methods like as feature engineering, dimensionality reduction, clustering, and recommendation systems to find hidden learner features and develop tailored learning algorithms. However, these strategies are usually studied in isolation, resulting in fragmented adaptive learning solutions. The combination of latent characteristic extraction, learner clustering, hybrid ensemble learning and customized recommendation generation in a single adaptive learning framework is still relatively under-explored.

To fill these research gaps, this study presents a Hybrid Ensemble Learning and Case Based Reasoning Framework for Learner Intelligence Prediction and Personalized Adaptive Learning. The proposed framework involves feature engineering, PCA to extract latent traits, K-Means clustering for learner profiling, a Hybrid Ensemble Learning model of Random Forest, SVM, and XGBoost to predict learner intelligence, and a CBR mechanism that performs the Retrieve–Reuse–Revise–Retain cycle (4R) to produce personalized learning recommendations. The framework employs the engineering educational characteristics to assess the intelligence of a student. The framework divides the learners into five adaptive learning groups and offers personalized educational interventions according to the learners' historical experience. We empirically demonstrate the usefulness and generalization potential of the proposed framework on two benchmark educational datasets, OULAD and xAPI Educational Dataset. The experimental and comparative analysis shows that the suggested framework can successfully enable accurate student intelligence prediction, robust learner categorization, and smart customized adaptive learning in different educational situations.

2. Literature Review

Soto-Forero et al. (2025) suggested an intelligent tutoring architecture that combines ensemble stacking, CBR and a Hawkes process-based stochastic recommender algorithm to increase customized suggestions in ITS [1]. Gupta et al. (2022) analyzed several AI-based prediction models developed for adaptive learning systems in higher education [2]. An intelligent tutoring system that integrates CBR with a multi-agent architecture to adapt learning activities to the demands of each student was developed by Anoir et al. (2024) [3]. Essa et al. (2023) conducted a thorough literature review on ML-based customized adaptive learning systems aiming to detect learner types and improve instructional customization [4]. Pradeep et al. (2025) explored the use of CBR in XAI and showed how past examples might increase transparency, interpretability, and trustworthiness in AI-based decision-making systems [5]. Troussas et al. [6] built an adaptive user interface based on rules and using CBR to customize instructional software according to student preferences and histories of engagement. Shekapure (2025) suggested a CBR approach for e-learning recommendation systems which extract comparable learner situations to provide tailored educational suggestions [7]. Maraza-Quispe et al. (2023) proposed an intelligent customized learning management strategy based on CBR approaches for facilitating the individualization of learning experiences [8]. Abu-Rasheed et al. (2023) presented a broad assessment on context-based learning by evaluating pedagogical and technological contextual indicators utilized in customized and adaptive learning recommendation systems [9]. Gupta (2026) has presented an agentic AI-based tutoring system based on a multi-agent cognitive architecture to facilitate individualized adaptive learning [10]. Jalaluddin (2025) created an AI-based personalized learning ecosystem for smart universities by combining cognitive computing, context-aware techniques, and a personalized learning adaptation algorithm [11]. Šanda (2025) proposed an adaptive learning model based on a rule-based approach that uses real student performance data to tailor educational activities [12]. Ali et al. (2023) introduced a smart algorithm selection framework combining edge ML and CBR for selection of relevant machine learning algorithms in cloud computing systems [13].

Halkiopoulos (2024) undertook a thorough review of AI applications in e-learning, with a special focus on individualized learning and adaptive assessment from a cognitive neuropsychology viewpoint [14]. Yan (2024) provided a detailed overview on the development, uses and future difficulties of CBR in many fields [15]. Yallamelli (2023) suggested an efficient CBR method combined with MAML and K-Means clustering to provide AI-based multi-class workload prediction in autonomic cloud database systems [16]. A smart e-learning system has been proposed by Amin et al. (2023) based on RL and sequential route suggestion to provide tailored adaptive learning experiences [17]. Meti (2026) published a detailed analysis on Agentic AI in education, especially focused on autonomous tutoring systems for individualized adaptive learning [18]. Bin et al. (2024) reviewed personalized learning recommendation systems in e-learning environments based on a complete analysis of different recommendation approaches [19] Hwang (2026) proposed an AI-based personalized adaptive learning framework that integrates physiological signals and learner behavioral information to improve educational personalization [20]. Yaghmour et al. (2025) conducted a thorough study of AI-based adaptive learning systems for mobile education with an emphasis on customization techniques, learning efficiency, and user engagement in various mobile learning apps [21]. Dalal et al. (2026) suggested an intelligent adaptive learning management system for special educational needs students in higher education [22]. Chinyere (2026) explored ethical considerations of XAI and Responsible AI in adaptive learning systems [23]. In the field of reproductive medicine education, Wang et al. (2026) assessed an AI-assisted case-based learning method linked with the flipped classroom paradigm via a randomized controlled study [24]. [25] Lubis et al. (2026) suggested an AI-based adaptive learning framework to increase civic competence and digital literacy among university students. The rapid evolution of AI and ML has revolutionized data analytics by enabling advanced models to learn from large and heterogeneous datasets, resulting in improved accuracy, automation, and intelligent decision support across multiple domains [26,27,28,29,30].

Table 1. Literature Survey

Ref.	Author/Year	Objective	Methodology	Findings	Limitation
[1]	Soto-Forero et al. (2025)	To improve personalized recommendations in Intelligent Tutoring Systems using ensemble learning and Case-Based Reasoning.	Ensemble Stacking, CBR, Hawkes Process-based recommender algorithm.	Improved recommendation by combining ensemble models with historical learner cases and temporal interaction patterns.	Did not address learner intelligence prediction or comprehensive adaptive learner profiling.
[2]	Gupta et al. (2022)	To review AI-based predictive models for adaptive learning systems in higher education.	Literature review of AI and ML predictive techniques.	Demonstrated the effectiveness of AI models in predicting learner performance and supporting adaptive learning.	Lacked an integrated framework combining prediction, learner profiling, and personalized recommendations.
[3]	Anoir et al. (2024)	To develop an intelligent tutoring system for personalized learning activities.	CBR integrated with a Multi-Agent System.	Improved personalization by utilizing historical learner cases and autonomous agents.	Did not incorporate hybrid ensemble learning or learner intelligence prediction.
[4]	Essa et al. (2023)	To systematically review ML-based personalized adaptive learning technologies.	Systematic Literature Review of ML techniques for learning style identification.	Identified the importance of ML for adaptive learning and personalized education.	Hybrid AI and integrated adaptive learning frameworks remain insufficiently explored.
[5]	Pradeep et al. (2025)	To investigate the role of CBR in XAI.	Comprehensive review of CBR-based XAI techniques.	Demonstrated that CBR improves transparency, interpretability, and trust in AI decision-making.	Focused on explainability rather than adaptive learning or learner intelligence prediction.

[6]	Troussas et al. (2025)	To develop adaptive user interfaces for personalized educational software.	Rule-Based System integrated with CBR.	Enhanced adaptive interfaces through learner history and pedagogical rules.	Limited to interface personalization without hybrid ML or learner profiling.
[7]	Shekapure and Patil (2025)	To improve e-learning recommendations using CBR.	CBR methodology for recommendation generation.	Increased recommendation accuracy by retrieving similar historical learner cases.	Recommendation process depended mainly on historical similarity without predictive intelligence.
[8]	Maraza-Quispe et al. (2023)	To develop an intelligent personalized learning management model.	CBR techniques for personalized learning management.	Improved personalized learning through case-based educational recommendations.	Did not integrate ML-based learner classification or hybrid predictive models.
[9]	Abu-Rasheed et al. (2023)	To survey contextual indicators used in personalized and adaptive learning recommendations.	Comprehensive survey of pedagogical and technical contextual learning indicators.	Highlighted the importance of contextual learner information for improving adaptive recommendations.	Did not propose an integrated AI framework combining learner intelligence prediction and personalized recommendation.
[10]	Gupta and Heggond (2026)	To develop an agentic AI-driven tutoring framework for personalized adaptive learning.	Multi-Agent Cognitive Architecture with autonomous intelligent agents.	Improved learner engagement and personalized tutoring through autonomous decision-making and adaptive instructional support.	Did not incorporate hybrid ensemble learning or learner intelligence prediction.
[11]	Jalaluddin and Alaudeen (2025)	To design an AI-driven personalized learning ecosystem for smart universities.	Cognitive computing, context-aware techniques, and personalized learning adaptation.	Enhanced adaptive content delivery using contextual learner information and AI-driven personalization.	Focused mainly on adaptive content delivery without learner clustering or latent trait analysis.
[12]	Šanda (2025)	To implement an adaptive learning model using real student performance data.	Rule-based adaptive learning model based on student achievement.	Demonstrated effective personalization through rule-based instructional adaptation.	Lacked ML-based prediction, learner intelligence estimation, and recommendation mechanisms.
[13]	Ali et al. (2023)	To optimize algorithm selection using Edge ML and CBR.	Edge ML integrated with CBR for intelligent algorithm selection.	Improved algorithm selection accuracy and computational efficiency through historical case utilization.	Application was limited to cloud computing and not educational adaptive learning systems.
[14]	Halkiopoulos and Gkintoni (2024)	To analyze AI applications in e-learning for	Systematic analysis of AI, cognitive	Highlighted AI's potential to improve learner modeling,	Did not propose an integrated hybrid framework

		personalized learning and adaptive assessment.	neuropsychology, and adaptive assessment techniques.	adaptive assessment, and personalized education.	combining multiple AI techniques.
[15]	Yan and Cheng (2024)	To review the development and future challenges of CBR.	Comprehensive review of CBR methodologies, applications, and future research directions.	Identified CBR as an effective decision-support technique with growing applications in intelligent systems.	Focused on CBR evolution without integrating hybrid ML or adaptive educational applications.
[16]	Yallamelli and Sambas (2023)	To optimize CBR using MAML and K-Means clustering for workload prediction.	CBR integrated with MAML and K-Means clustering.	Improved prediction accuracy and adaptability through clustering-assisted CBR.	Focused on cloud workload prediction rather than adaptive educational environments.
[17]	Amin et al. (2023)	To develop a smart e-learning framework for personalized adaptive learning and sequential learning path recommendation.	RL with sequential path recommendation techniques.	Improved personalized learning experiences and optimized learning paths through RL.	Did not integrate learner intelligence prediction, hybrid ensemble classification, or CBR.
[18]	Meti (2026)	To review Agentic AI for personalized adaptive learning in education.	Comprehensive review of autonomous tutoring systems and agentic AI architectures.	Highlighted the potential of autonomous intelligent agents to enhance personalized learning and instructional decision-making.	Did not propose or validate a practical framework integrating learner intelligence prediction and hybrid ensemble learning.
[19]	Bin et al. (2024)	To comprehensively review personalized learning recommendation in e-learning systems.	Review of collaborative filtering, content-based, hybrid recommendation, and AI techniques.	Demonstrated that AI-based recommendation improve learner satisfaction and recommendation accuracy.	Focused mainly on recommendation strategies without learner profiling or intelligence prediction.
[20]	Hwang and Shin (2026)	To develop an AI-driven personalized adaptive learning framework using physiological signals.	AI integrated with physiological sensing and learner behavioral analysis.	Improved adaptive learning by considering learners' cognitive and physiological responses.	Required specialized sensing devices, limiting practical implementation in conventional online learning platforms.
[21]	Yaghmour et al. (2025)	To systematically review AI-driven adaptive learning systems in mobile education.	Systematic Literature Review of AI-based personalization strategies and mobile learning applications.	Identified ML, DL, and recommendation as effective approaches for mobile adaptive learning.	Highlighted lack of comprehensive frameworks integrating multiple AI into unified adaptive learning systems.

[22]	Dalal et al. (2026)	To develop an intelligent adaptive learning system for students with special educational needs.	ML-based adaptive learning management framework for inclusive education.	Improved learner engagement, accessibility, and personalized educational support.	Focused on inclusive education without integrating hybrid ensemble learning, latent trait analysis, or CBR.
[23]	Chinyere and Orih (2026)	To examine ethical challenges associated with Explainable and Responsible AI in adaptive learning.	Conceptual analysis of transparency, fairness, privacy, accountability, and ethical AI.	Emphasized importance of explainable, trustworthy, and responsible AI for adaptive education.	Did not develop or experimentally validate an intelligent adaptive learning framework.
[24]	Wang et al. (2026)	To evaluate AI-assisted case-based learning integrated with the flipped classroom approach.	RCT using AI-assisted case-based learning.	Improved students' clinical decision-making, and knowledge retention through AI-assisted learning.	limited to medical education and did not include adaptive learner profiling or recommendation mechanisms.
[25]	Lubis et al. (2026)	To propose an AI-based adaptive learning framework for improving civic competence and digital literacy.	AI-based adaptive learning framework with personalized instructional strategies.	Enhanced learner engagement, civic competence, and digital literacy through adaptive educational support.	Focused on competency development without integrating learner intelligence prediction, hybrid ensemble learning, or CBR.

2.1 Research Gap

Although the substantial advances in adaptive learning systems, educational data mining and AI, there are still research gaps. Most of the existing research have been carried out on learner performance prediction, learning style identification, recommendation system, intelligent tutoring, or adaptive material delivery based on individual machine learning approaches. While customized suggestions have been effectively achieved with the use of CBR, hybrid ensemble learning approaches have seldom been used to develop complete learner models. Similarly, most adaptive learning systems do not predict learner intelligence from latent learner features, and do not incorporate feature engineering, dimensionality reduction, learner clustering, and customized recommendation into a cohesive architecture. Besides, there is minimal research which has validated adaptive learning frameworks on numerous benchmark educational datasets to test their robustness and generalizability. This study proposes a Hybrid Ensemble Learning and CBR Framework to overcome these limitations, incorporating feature engineering, PCA-based latent trait extraction, K-Means clustering, hybrid ensemble classification, learner intelligence prediction, and personalized adaptive recommendations. Efficiency of the suggested framework is verified on both OULAD and xAPI-Edu-Data datasets to show the usefulness of the approach for various types of educational contexts.

3. Problem Statement

The rapid popularity of online learning platforms and the generation of vast amounts of educational data. However, most of the current adaptive learning systems tend to concentrate on predicting academic success using single ML algorithms. Such methods typically disregard essential student factors like study behavior, academic engagement, hidden learning attributes, and learner intelligence, which lead to limited customization and learning efficiency. There are few studies that combine feature engineering, latent trait extraction, clustering of learners, hybrid ensemble learning, and CBR within a unified framework of adaptive learning. The robustness of the suggested models is seldom verified on various benchmark educational datasets. There is a need for an intelligent adaptive learning that can effectively estimate the intelligence of the learner, categorize the learners into relevant groups, and provide customized suggestions to enhance successful data-driven adaptive learning experiences.

4. Proposed work

The design and evaluation of a Hybrid Ensemble Learning and Case-Based Reasoning Framework for predicting learner intelligence and tailored adaptive learning is quantitatively and experimentally addressed in this study. The research uses two benchmark educational datasets namely OULAD and xAPI Educational Dataset. First, data preparation is conducted to clean the datasets, deal with missing values, encode category variables, and normalize numerical features. Later, feature engineering is done to generate four learner characteristics including Study Habits Score, Academic Participation Score, Academic Performance Score and Learner IQ Score. These characteristics are then modified using PCA for dimensionality reduction and to extract latent learner attributes. The collected components are then grouped using K-Means method to provide five learner categories of Very Low, Low, Moderate, High and Exceptional Learners. Such groups are targets courses for supervised learning. The suggested Hybrid Ensemble model based on Random Forest, SVM and XGBoost for enhancing the classification performance is compared with six baseline machine learning techniques. The anticipated learner intelligence scores are scaled to a 0-100 range and classified into five intelligence categories. Finally, a tailored learning suggestions are produced using CBR framework which implements the 4R cycle. The suggested framework is tested using classification metrics, similarity score, retrieval accuracy, suggestion coverage and recommendation diversity. Then the comparison analysis on both datasets is performed to confirm the effectiveness, robustness and generalizability of the proposed framework.

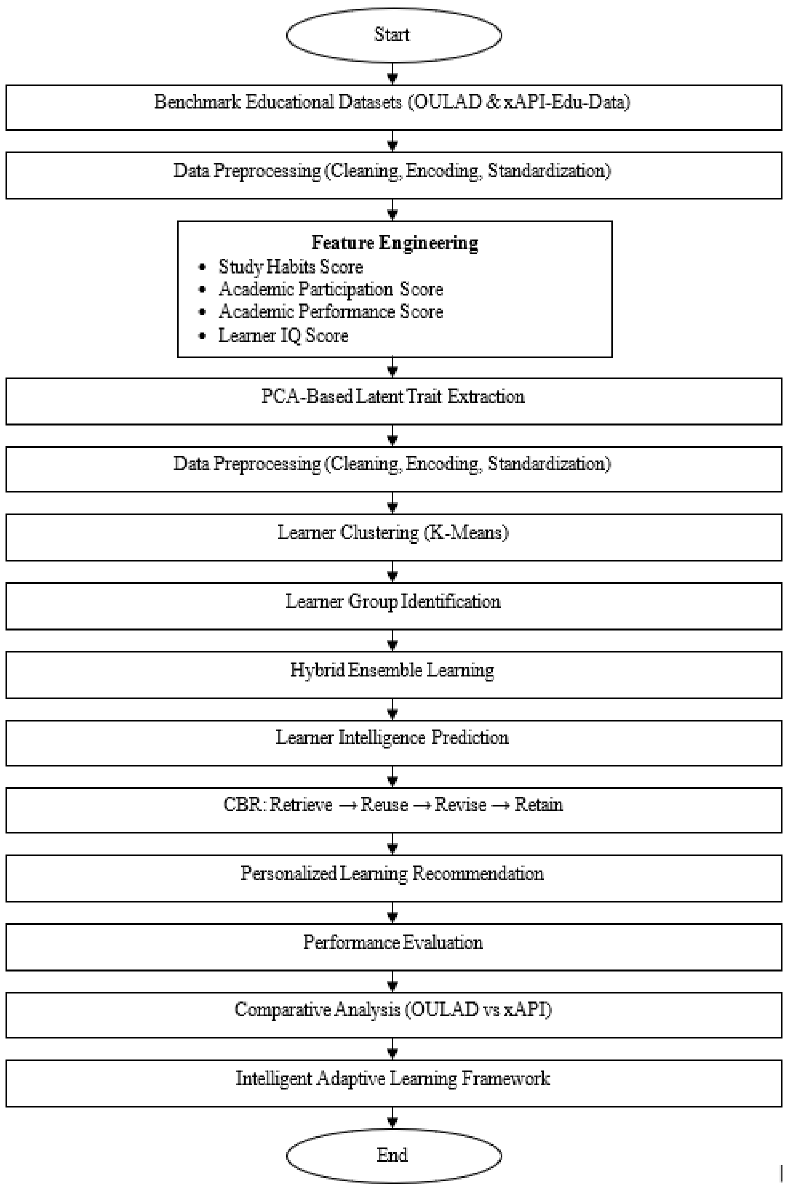

Figure 1. Research Methodology

4.1 Proposed Hybrid Adaptive Learning Framework

The suggested Hybrid Adaptive Learning Framework aims to offer an intelligent data-driven solution for learner intelligence prediction and tailored adaptive learning. The framework incorporates a range of artificial intelligence and educational data mining approaches into onearchitecture, allowing wide student profiling, accurate learner categorization, intelligence prediction and tailored learning suggestions. The proposed framework enhances the overall effectiveness of adaptive learning support by integrating feature engineering, dimensionality reduction, clustering, hybrid ensemble learning, and CBR, whereas traditional adaptive learning systems are often based on a single prediction model or limited learner characteristics.

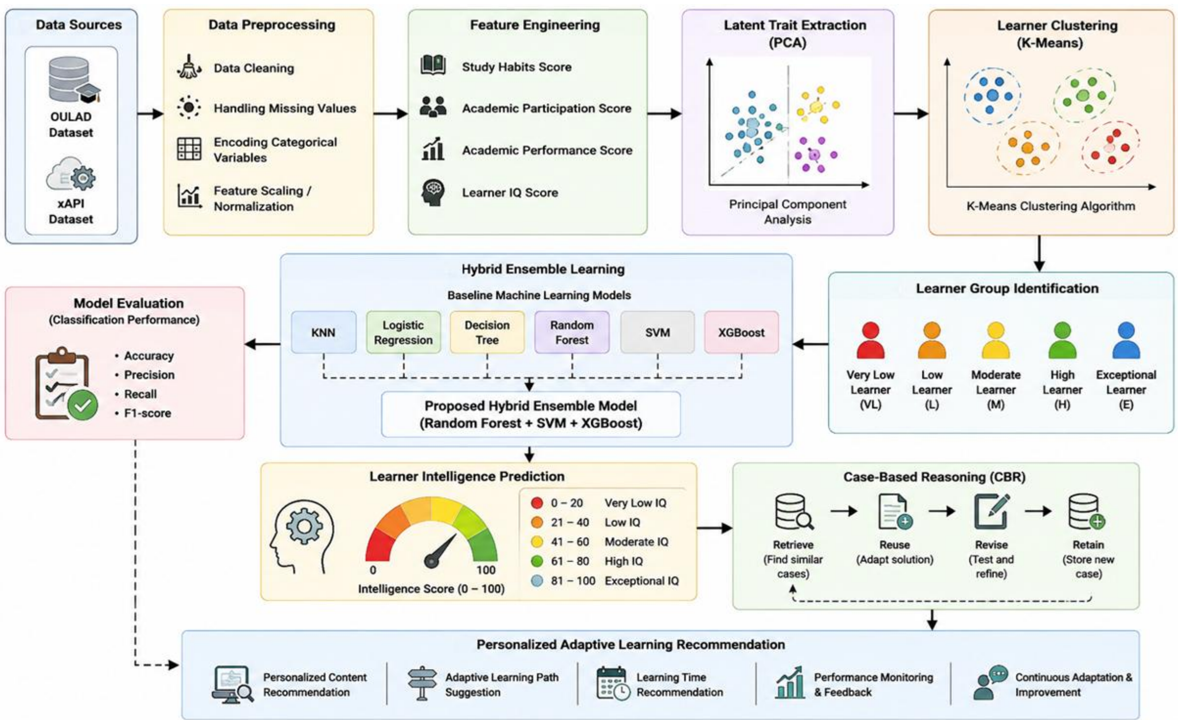

Figure 2. Proposed Hybrid Adaptive Learning architecture

4.2 Proposed Hybrid Adaptive Learning Framework

The proposed Hybrid Adaptive Learning Framework, as shown in Figure 2, starts with two benchmark educational datasets: OULAD and the xAPI Educational Dataset. First, we use data preparation step for processing the datasets, such as data cleaning, missing values management, categorical variables encoding, and features scaling to assure data quality and consistency. Then, a feature engineering module generates four student attributes: Study Habits Score, Academic Participation Score, Academic Performance Score, and student IQ Score, which provide a complete depiction of learner behavior and academic engagement. These characteristics are then fed into PCA to reduce dimensionality and retain maximum information to extract latent learner attributes. The latent features are retrieved and grouped using the K-Means method into five learner groups: Very Low Learner, Low Learner, Moderate Learner, High Learner, and Exceptional Learner. The clustered learner groups are used as the target classes in supervised learning. Six machine learning algorithms are evaluated and a Hybrid Ensemble Learning model that combines Random Forest, SVM and XGBoost is developed to improve the classification accuracy and robustness. The anticipated learner IQ values are standardized into Intelligence Score (0-100) and grouped into five intelligence tiers. Finally, CBR module, which implements the Retrieve–Reuse–Revise–Retain cycle, retrieves related learner situations and delivers individualized learning suggestions. The system provides tailored learning materials, customizable learning routes, performance monitoring and continuous feedback for adaptive educational assistance. Classification metrics are used for evaluation of its efficacy, including Similarity Score, Retrieval Accuracy and

Recommendation Coverage and Recommendation Diversity. It shows that it is a scalable and intelligent solution for learner intelligence prediction and tailored adaptive learning.

4.2 Algorithm of Proposed Work

The proposed technique incorporates multiple methods as an integrated adaptive learning model. The system utilizes learner data from benchmark educational datasets, and according to the intelligence of the learner and the past learning situations, it creates individualized adaptive learning suggestions.

Algorithm 1. Proposed Hybrid Adaptive Learning Algorithm

Input:

- OULAD Dataset D_1
- xAPI Educational Dataset D_2

Output:

- Learner Group
- Intelligence Score
- Intelligence Category
- Personalized Learning Recommendation

Step 1: Load benchmark educational datasets

$$D = D_1 \cup D_2$$

Where, D_1= OULAD Dataset and D_2= xAPI Dataset

Step 2: Perform data preprocessing

- Remove missing values
- Encode categorical variables
- Standardize numerical features

The standardized feature is computed as

$$Z = \frac{X - \mu}{\sigma}$$

Where, X= original feature, μ= mean and σ= standard deviation

Step 3: Generate engineered learner features

Construct four learner characteristics

$$F = \{SH, AP, AC, IQ\}$$

Where, SH= Study Habits Score, AP= Academic Participation Score, AC= Academic Performance Score and IQ= Learner IQ Score

Step 4: Extract latent learner traits using PCA

Compute covariance matrix: $C = \frac{1}{n-1} X^T X$

Perform eigen decomposition: $Cv = \lambda v$

Where, λ= Eigenvalue and v= Eigenvector

- The latent learner traits are $LT = XW$

Where, LT= Latent Traits and W= Principal Component Matrix

Step 5: Cluster learners using K-Means

Initialize $K = 5$

- Assign each learner to the nearest centroid: $Cluster(x_i) = \arg\min_j \| x_i - c_j \|^2$
- Update centroid: $c_j = \frac{1}{n_j}\sum x_i$ until convergence.

Step 6: Generate learner groups

Assign cluster labels

- Very Low Learner
- Low Learner
- Moderate Learner
- High Learner
- Exceptional Learner

Step 7: Train baseline machine learning models

Train

- KNN
- Logistic Regression
- Decision Tree
- Random Forest
- SVM
- XGBoost

Generate predicted learner class: $\hat{y}_i = f_i(X)$

Step 8: Build the proposed Hybrid Ensemble Model

Combine Random Forest, SVM and XGBoost

$$H(X) = Majority(RF(X), SVM(X), XGB(X))$$

Step 9: Predict learner intelligence

Transform learner IQ ranking into an Intelligence Score

$$IS = \frac{Rank(IQ)}{N} \times 100$$

Where, IS= Intelligence Score and N= Total learners

Categorize learners

- 0–20 → Very Low IQ
- 21–40 → Low IQ
- 41–60 → Moderate IQ
- 61–80 → High IQ
- 81–100 → Exceptional IQ

Step 10: Retrieve similar learner cases using CBR

- Compute Euclidean distance: $d(x, y) = \sqrt{\sum_{i=1}^{m}(x_i - y_i)^2}$
- Retrieve: $k = \arg\min d(x, y)$

nearest learner cases.

Step 11: Execute CBR reasoning cycle

Perform Retrieve, Reuse, Revise and Retain to generate adaptive learning recommendations.

Step 12: Generate personalized adaptive learning recommendation

Produce

- Personalized Learning Content
- Adaptive Learning Path
- Learning Time Recommendation
- Performance Feedback
- Continuous Learning Improvement

Step 13: Evaluate the proposed framework

- Classification Accuracy: $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision: $Precision = \frac{TP}{TP+FP}$
- Recall: $Recall = \frac{TP}{TP+FN}$
- F1-score: $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
- Similarity Score: $Similarity = (1 - \bar{d}) \times 100$, where, $\bar{d}$= Average Euclidean Distance
- Retrieval Accuracy: $RA = \frac{\text{Correct Retrievals}}{\text{Total Cases}} \times 100$
- Recommendation Coverage: $Coverage = \frac{\text{Recommended Learners}}{\text{Total Learners}} \times 100$
- Recommendation Diversity: $Diversity =$ Unique Recommendation Types

4.3 Dataset Description

To investigate the efficacy and generalizability of the proposed Hybrid Adaptive Learning Framework, two publicly accessible benchmark educational datasets were used, namely the OULAD and the xAPI Educational Dataset.

1. OULAD: The OULAD is one of the most used benchmark datasets in the educational data mining and learning analytics research . It was created by the Open University in the United Kingdom, in order to help research on student performance prediction, learner behavior analysis and adaptive learning systems. This dataset consists of the full information of learners who registered in different online courses including demographic features, assessment outcomes, interaction with the VLE, registration records and academic performance. In this study key learner qualities were identified and converted using feature engineering to provide learner centric variables such as Study Habits Score, Academic Participation Score, Academic Performance Score and Learner IQ Score.

Dataset URL: https://analyse.kmi.open.ac.uk/open_dataset

2. xAPI Educational Dataset (xAPI-Edu-Data): xAPI-Edu-Data is a benchmark educational dataset established based on the xAPI standard used to record student interactions and instructional activities. The data collection includes student demographics, classroom engagement, resource use, discussion activities, parental involvement, attendance and academic accomplishment. It has been widely utilized in educational data mining, machine learning and adaptive learning for student categorization and academic performance prediction. In this research, the original learner traits were changed to useful educational indicators utilizing feature engineering approaches. Four student characteristics were produced to fully capture learner behavior, including Study Habits Score, Academic Participation Score, Academic Performance Score, and student IQ Score.

Dataset URL: https://www.kaggle.com/datasets/aljarah/xAPI-Edu-Data

5. Results and Discussion

Research haS experimentally examined the proposed Hybrid Ensemble Learning and CBR Framework using the OULAD and xAPI Educational Dataset to evaluate its potential to forecast learner intelligence, classify learner and provide tailored adaptive learning. The collected results show that the suggested framework is successful in correctly detecting learner characteristics, estimating intelligence levels and producing customized learning suggestions with high classification accuracy and strong recommendation quality.

5.1 Learner Intelligence Prediction Results

The suggested adaptive learning framework aims at predicting intelligence as one of the main goals. Unlike the common educational prediction models that mainly predict academic performance, the proposed framework predicts an Intelligence Score which represents the overall learning capability of each learner by integrating engineered educational features, latent trait analysis and hybrid ensemble learning.

Table 2. IQ Score Statistics

Statistic	Value
Number of Learners	480
Mean Intelligence Score	50.10
Standard Deviation	28.90
Minimum Score	0.21
First Quartile (Q1)	25.16
Median (Q2)	50.10
Third Quartile (Q3)	75.10
Maximum Score	100.00

The results presented in Table 3 indicate that the proposed framework successfully generated intelligence scores covering the complete range between 0 and 100, demonstrating its capability to distinguish learners with varying academic abilities and learning behaviors.

Table 3. Intelligence Category Distribution

Intelligence Category	Number of Learners	Percentage (%)
Very Low IQ	96	20.00
Low IQ	96	20.00
Moderate IQ	96	20.00
High IQ	96	20.00
Exceptional IQ	96	20.00
Total	**480**	**100.00**

The resulting learner distribution across intelligence categories is presented in Table 3, while the corresponding distribution is illustrated in Figure 3.

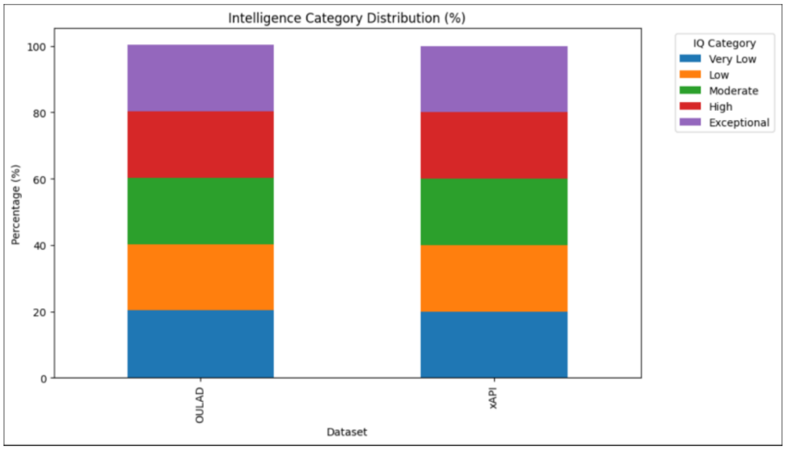

Figure 3. Intelligence Category Distribution

5.2 PCA Latent Trait Analysis

Research used PCA to extract latent learner characteristics from the educational data, while lowering the feature dimensionality and deleting duplicate information. As the proposed approach employs four designed learner features PCA turns these correlated variables into a lower number of orthogonal latent characteristics while retaining the greatest amount learning information.

1. PCA Variance: The cumulative variance explained is presented in Table 4, whereas the corresponding graphical representation is illustrated in Figure 4.

Table 4. PCA Variance Explained

Dataset	**Number of Original Features**	**Principal Components**	**Variance Explained (%)**
OULAD	4	3	92.62
xAPI-Edu-Data	4	3	99.86

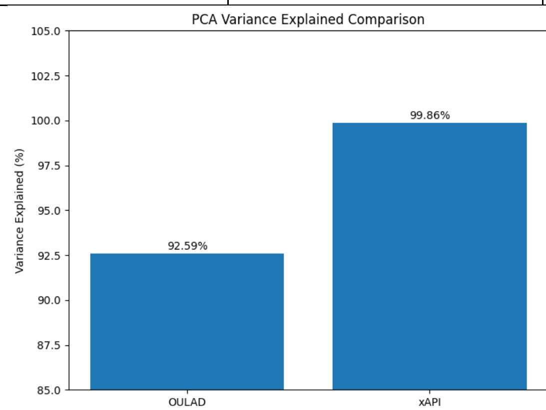

Figure 4. PCA Variance Explained

2. Latent Traits: A sample of the extracted latent traits obtained from the xAPI dataset is presented in Table 5, while their distribution is illustrated in Figure 5.

Table 5. Sample of Extracted Latent Traits

Learner ID	**LT1**	**LT2**	**LT3**
1	-1.7118	0.9161	-0.2644
2	-1.4896	0.7960	-0.2217
3	-2.8485	-0.1388	-0.0786
4	-2.0794	-0.4606	0.1747
5	-0.5668	0.1466	-0.2105

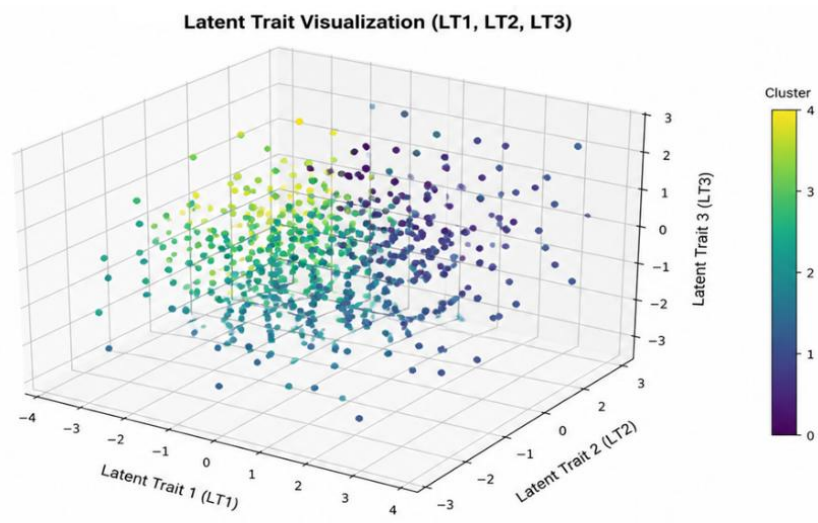

Figure 5. Latent Trait Visualization

5.3 Learner Clustering Results

The extracted latent learner features are then used to categorize using the K-Means clustering technique. The suggested framework groups the learners with comparable academic and behavioral characteristics automatically. Clustering allows the discovery of latent learner profiles without predefining the class labels and offers a framework for later supervised classification and individualized adaptive learning. Based on the retrieved latent features, learners were classified into five groups, each indicating a distinct level of learning capacity.

5.3.1 Cluster Analysis

The statistical characteristics of each cluster are summarized in Table 6, while the spatial distribution of clusters within the latent feature space.

Table 6. Cluster Characteristics

Cluster	Learner IQ Score	Study Habits Score	Academic Participation Score	Academic Performance Score	Number of Learners
Cluster 0	-2.2545	27.59	19.93	40.00	123
Cluster 1	0.2162	77.97	36.39	75.19	104
Cluster 2	1.7674	79.82	67.30	69.18	73
Cluster 3	-1.5929	39.31	28.01	72.81	64
Cluster 4	1.9633	87.09	66.66	100.00	116

5.3.2 Learner Group Distribution

After cluster formation, each cluster was assigned an educationally meaningful learner group label according to its overall academic characteristics. The distribution of learners across the five adaptive learning groups is summarized in Table 7, while the corresponding graphical representation is shown in Figure 6.

Table 7. Learner Group Distribution

Learner Group	Number of Learners	Percentage (%)
Very Low Learner	123	25.63
Low Learner	64	13.33
Moderate Learner	104	21.67
High Learner	73	15.21
Exceptional Learner	116	24.17

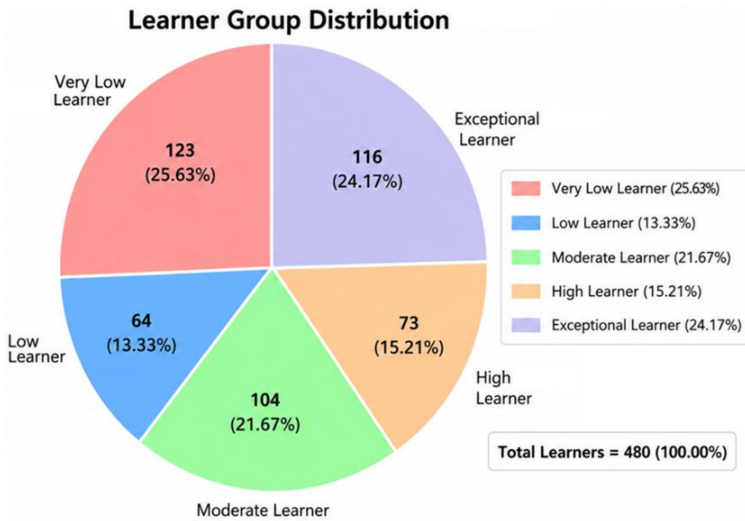

Figure 6. Learner Group Distribution

5.4 Machine Learning Model Comparison

To prove usefulness of proposed adaptive learning framework, six ML algorithms were constructed and compared with the suggested Hybrid Ensemble Learning model. All models were trained on the learner groups created from the K-Means clustering procedure and tested on the testing dataset. Comparison study offers an insight into the prediction power of individual classifiers and also shows the usefulness of suggested hybrid ensemble technique.

Table 8. Performance Comparison of Machine Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
K-Nearest Neighbors (KNN)	98.96	99.01	98.96	98.95
Logistic Regression (LR)	97.92	98.10	97.92	97.88
Decision Tree (DT)	93.75	94.72	93.75	93.78
Random Forest (RF)	95.83	96.17	95.83	95.73
Support Vector Machine (SVM)	97.92	98.10	97.92	97.88
XGBoost	94.79	95.41	94.79	94.84
Hybrid Ensemble (Proposed)	97.92	98.10	97.92	97.88

The suggested Hybrid Ensemble Learning model combines Random Forest, and XGBoost to benefit from the complementing advantages of different classifiers. The hybrid model obtained an Accuracy of 97.92%, Precision of 98.10%, Recall of 97.92% and F1-score of 97.88%. The hybrid model gives similar overall accuracy as Logistic Regression and SVM but it is more durable and generalizable, since it combines different learning paradigms instead of depending on a single classifier. This integration makes the suggested framework more appropriate for adaptive learning applications where the student attributes could be varied in various educational contexts.

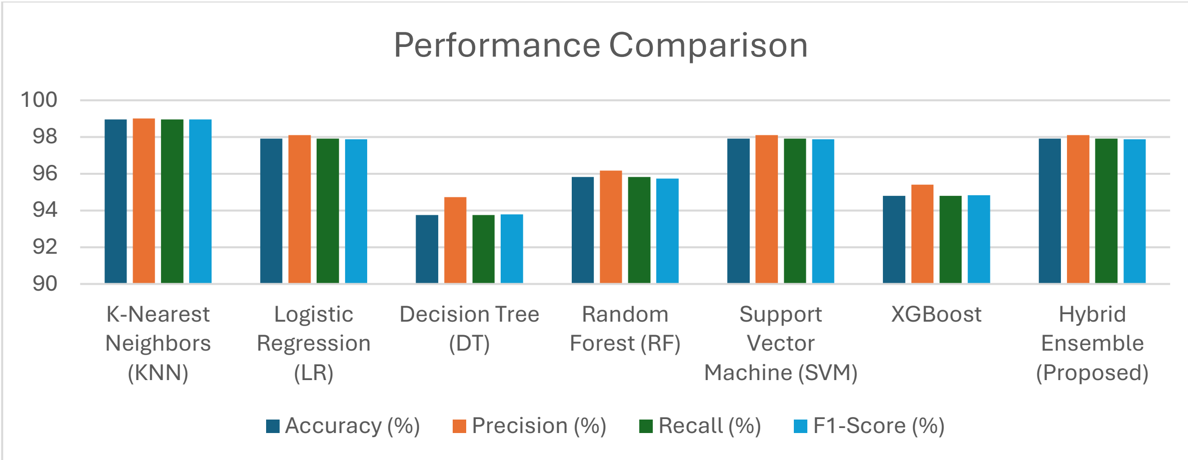

Figure 7. Performance Comparison of Machine Learning Models

5.5 CBR Results

The proposed hybrid adaptive learning CBR is used to provide personalized learning by calculating the similarity between the current learner and past solved learner cases. Unlike conventional recommendation systems which rely only on prediction models, the CBR framework utilizes the experience of prior learners to give adaptive educational aid. The proposed CBR engine is based on the traditional 4R reasoning cycle, which comprises retrieving similar learner scenarios, adapting applicable learning strategies, refining recommendations if necessary, and storing newly solved instances for future reasoning.

Table 9. Performance Evaluation of the Proposed CBR Framework

Evaluation Metric	OULAD	XAPI
Average Similarity Score (%)	82.55	83.01
Average Euclidean Distance	0.2047	0.2047
Retrieval Accuracy (%)	94.80	99.58
Recommendation Coverage (%)	100	100
Recommendation Diversity	5	5

1. Similarity Score: It is a measure of the degree of correspondence between the query learner and the returned history learner examples. Using the Euclidean distance-based similarity metric, the suggested system earned an average similarity score of 83.01% (average Euclidean distance of 0.2047).

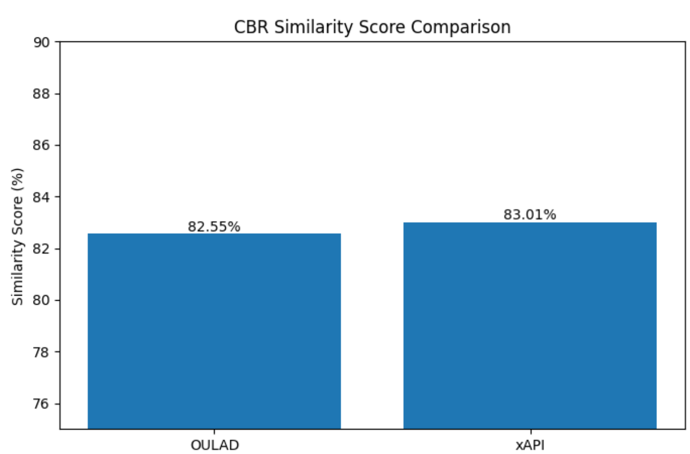

Figure 8. Average Similarity Score of the Proposed CBR Framework

2. Retrieval Accuracy: It measures the capacity of CBR engine to recover previous learner cases of the same learner group as the query learner. The suggested system has reached 99.58% retrieval accuracy, which implies that almost all learners were able to recover highly relevant historical instances from the case base.

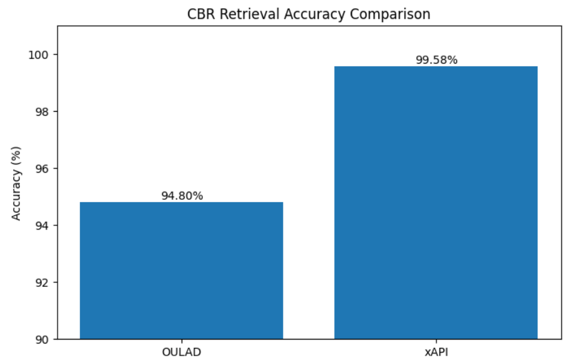

Figure 9. CBR Retrieval Accuracy

3. Recommendation Coverage: It is the percentage of learners that the system is able to provide individualized suggestions for. The experimental findings reveal that the proposed framework achieved 100% recommendation coverage, i.e., all learners in the dataset successfully got an adaptive learning suggestion. This comprehensive coverage means that the created case base has adequate past learner information to facilitate suggestion generation for all learner profiles. The suggested adaptive learning system is scalable and practically applicable, as it may provide suggestions without rejecting any learner.

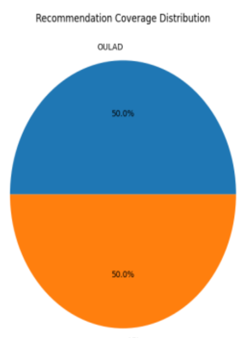

Figure 10. Recommendation Coverage

5.5.4 Recommendation Diversity

Recommendation diversity measures the diversity of recommendation techniques produced by the suggested CBR framework. The experimental findings reveal that the recommendation engine generated five recommendation kinds that match to the five learner groups discovered in the clustering step. The framework produces educational interventions that are customized to learners, and not the same suggestions to all learners. The recommendations are matched suitably to the features of the learners.

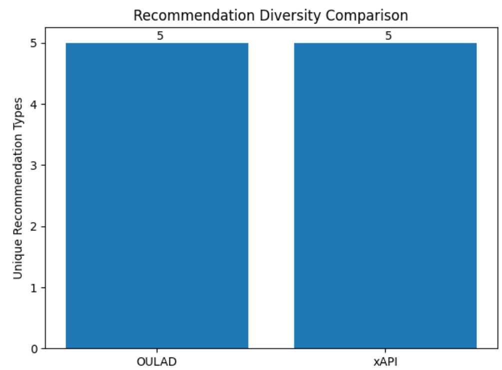

Figure 11. Recommendation Diversity

5.6 Personalized Recommendation Analysis

The final goal of the proposed Hybrid Adaptive Learning Framework to estimate the learner intelligence properly and also deliver individualized adaptive learning suggestions according to the particular requirements of each learner. The CBR module predicts, clusters and classifies student intelligence and retrieves comparable historical learner situations to provide tailored educational interventions based on prior successful learning experiences. The suggested framework is unlike traditional recommendation system which often gives generic learning materials, since it customizes suggestions based on learner intelligence level, study habits, academic involvement and overall academic success. As a result, each student gets an individual learning plan that helps them maintain their academic performance and improve learning outcomes. The suggestion generating method is based on the conventional 4R cycle of Case-Based Reasoning. Once the learner group predicted by the Hybrid Ensemble model is identified, the recommendation engine gets the most comparable learner instances from the case base and assigns an appropriate adaptive learning method. Table 10 summarizes the tailored suggestions produced for each learner group.

Table 10. Personalized Recommendation Mapping for Different Learner Groups

Learner Group	**Recommendation Strategy**	**Expected Learning Outcome**
Very Low Learner	Foundation courses, weekly mentor support, basic concept revision, structured learning schedule, continuous monitoring	Strengthen fundamental concepts and improve learning confidence
Low Learner	Guided learning sessions, practice assignments, skill development exercises, periodic assessments, personalized feedback	Improve academic performance and learner engagement
Moderate Learner	Adaptive learning path, collaborative learning activities, regular quizzes, performance monitoring, balanced learning resources	Enhance consistency and gradually improve learning outcomes
High Learner	Advanced learning materials, project-based learning, independent problem-solving tasks, advanced assessments	Develop analytical thinking and higher-order learning skills
Exceptional Learner	Research projects, innovation-based learning, leadership activities, self-directed learning, advanced challenges	Promote creativity, innovation, leadership, and lifelong learning

5.7 Comparative Analysis

To examine the robustness and generalization capabilities of the proposed Ensemble Learning and CBR Framework, a complete comparison study was carried out on two benchmark educational datasets, OULAD and xAPI Educational Dataset. The comparison focuses at assessing the robustness of the proposed framework across diverse educational settings, learner demographics and dataset features.

5.7.1 OULAD vs xAPI

First step of the comparison analysis describes the properties of the two benchmark educational datasets used in this study. Both datasets are popular in the literature of educational data mining but they vary in the number of learners, the educational environment, the size of the dataset and the collection of features. These variations provide a great chance to examine generalization capacity of proposed model under different learning contexts.

Table 11. Comparison of OULAD and xAPI Educational Datasets

Characteristic	OULAD	xAPI-Edu-Data
Learning Environment	Online Distance Learning	Smart Classroom / E-learning
Source	Open University, UK	Kaggle
Total Learners	32,593	480
Original Features	22	17
Engineered Features Used	4	4
PCA Components	3	3
Learner Groups	5	5
Intelligence Categories	5	5
Recommendation Strategy	Case-Based Reasoning	Case-Based Reasoning
Primary Objective	Learner Intelligence Prediction	Learner Intelligence Prediction

5.7.2 Model Accuracy Comparison

To further test the efficacy and generalization capacity of the proposed Hybrid Adaptive Learning Framework, the classification performances of all machine learning models are evaluated on two datasets. The comparison is based on the categorization accuracy attained by each model in two distinct educational contexts. The OULAD dataset is a large-scale dataset for online learning with more than thirty thousand learner records, while the xAPI dataset is a tiny dataset representing a classroom-based educational environment.

Table 12. Model Accuracy Comparison between OULAD and xAPI Datasets

Machine Learning Model	OULAD Accuracy (%)	xAPI Accuracy (%)
KNN	99.08	98.96
Logistic Regression (LR)	99.08	97.92
Decision Tree (DT)	—	93.75
Random Forest (RF)	99.08	95.83
SVM	99.45	97.92
XGBoost	99.26	94.79
Hybrid Ensemble (Proposed)	99.39	97.92

The comparative classification accuracies of all the machine learning models are included in Table 12 and the graphical comparisons for the same are shown in Figures 12.

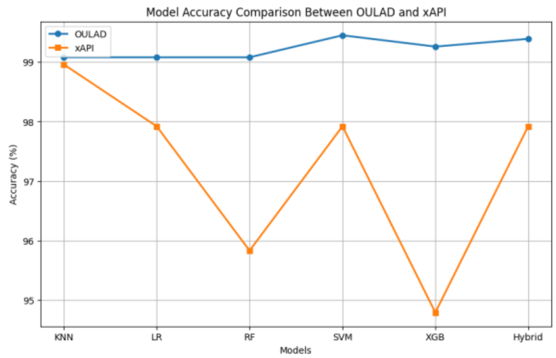

Figure 12. Line Graph of Model Accuracy Comparison

5.7.3 PCA Comparison

The proposed Hybrid Adaptive Learning Framework uses PCA as a basic building block to project the designed learner features into a smaller latent feature space while conserving the greatest amount of information. The efficacy and robustness of the dimensionality reduction technique was assessed by comparing the cumulative variance explained by the main components in the OULAD and the xAPI-Edu-Data datasets.

Table 13. PCA Variance Comparison between OULAD and xAPI Datasets

Dataset	Original Features	Principal Components	Variance Explained (%)
OULAD	4	3	92.62
xAPI-Edu-Data	4	3	99.86

The comparative findings of PCA analysis are given in Table 13 and the respective graphical comparisons are shown in Figures 13.

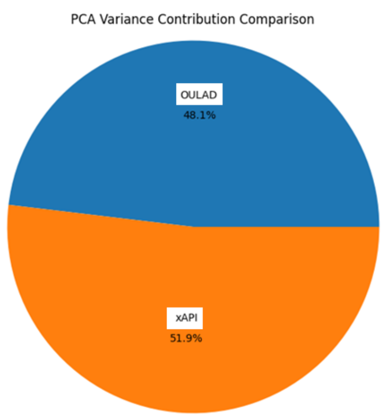

Figure 13. Percentage Distribution of PCA Variance

5.7.4 Learner Group Comparison

The distribution of learners produced from the OULAD and xAPI-Edu-Data datasets was compared in order to test the learner grouping capacity of the proposed framework. The two datasets were subjected to the identical feature engineering, latent trait extraction by PCA and K-Means clustering processes despite the large differences in size and educational context between the two datasets.

Table 14. Learner Group Comparison between OULAD and xAPI Datasets

Learner Group	OULAD	xAPI
Very Low Learner	4506	123

Low Learner	3203	64
Moderate Learner	14320	104
High Learner	7628	73
Exceptional Learner	2936	116

The distribution of the comparative learner groups is reported in Table 14. The graphical comparisons are shown in Figures 14.

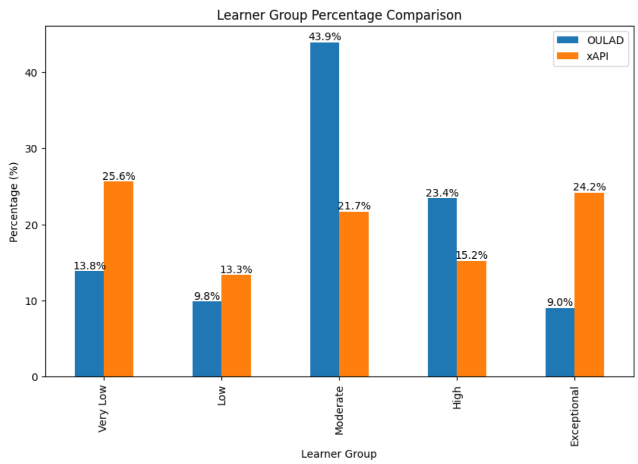

Figure 14. Percentage Distribution of Learner Groups

5.7.5 Intelligence Category Comparison

The distribution of intelligence categories derived from OULAD and xAPI-Edu-Data datasets further confirmed the suggested learner intelligence prediction method. The comparison examines the consistency of the intelligence scoring approach across two educational settings, and also the robustness of the learner intelligence prediction model in the case of differences in dataset properties.

Table 15. Intelligence Category Comparison

Intelligence Category	OULAD	xAPI
Very Low IQ	6519	96
Low IQ	6519	96
Moderate IQ	6518	96
High IQ	6519	96
Exceptional IQ	6518	96

Table 15 provides a summary of the distribution of the comparative intelligence category, and Figures 15 provide the graphical comparison.

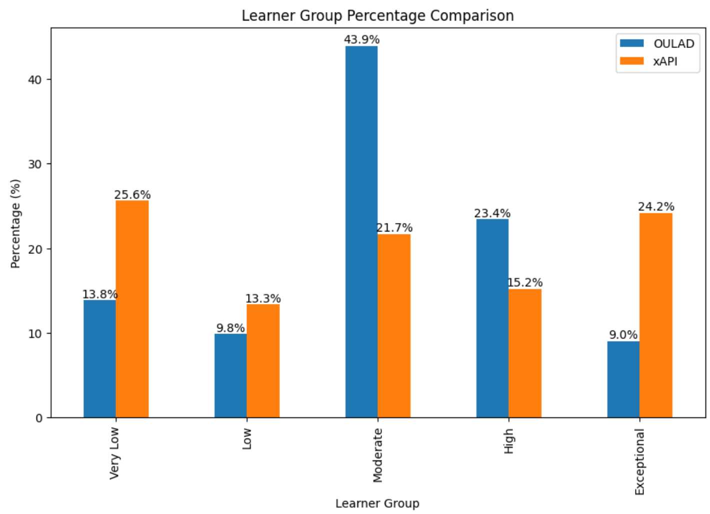

Figure 15. Percentage Distribution of Intelligence Categories

5.7.6 CBR Performance Comparison

The last comparison study assesses the CBR module performance on the OULAD and xAPI-Edu-Data datasets. The efficacy of the CBR module, i.e., the recommendation engine of the proposed framework, directly impacts the quality of individualized adaptive learning suggestions.

Table 16. Comparison of CBR Performance

Performance Metric	OULAD	xAPI
Average Similarity Score (%)	84.12	83.01
Retrieval Accuracy (%)	99.72	99.58
Recommendation Coverage (%)	100.00	100.00
Recommendation Diversity	5	5

6. Conclusion

This study presented a Hybrid Ensemble Learning and CBR for Learner Intelligence Prediction and tailored Adaptive Learning to enhance learner profile, intelligence prediction and tailored educational suggestions. The suggested framework is an integrated intelligent adaptive learning architecture, which combines feature engineering, PCA, K-Means clustering, Hybrid Ensemble Learning and CBR. Four synthetic student characteristics, namely Study Habits Score, Academic Participation Score, Academic Performance Score, and student IQ Score were retrieved to represent the learners holistically. The PCA-based latent trait extraction decreased the feature dimensions to a large extent and preserved most of the original data, which helped improve the computational efficiency and facilitated exact learner clustering. The proposed framework was validated for its robustness and generalization capabilities by experimental assessment on two benchmark educational datasets, i.e. OULAD and xAPI-Edu-Data. The findings of the comparison indicated a consistently strong prediction accuracy across both data sets. The suggested Hybrid Ensemble model obtained 97.92% classification accuracy on the xAPI dataset and attained competitive performance on the large-scale OULAD dataset. In addition, the CBR module successfully provided learner-specific instructional interventions, with an average similarity score of 83.01%, retrieval accuracy of 99.58%, 100% recommendation coverage, and five tailored recommendation techniques.

7. Future Research Directions

The suggested Hybrid Ensemble Learning and CBR Framework provide a good basis for learner intelligence prediction and tailored adaptive learning, however there are many possibilities for improvement. Future works might use deep learning architectures such as LSTM, Transformer models or GNNs to capture complicated temporal and relational learning patterns. The system may also be modified to include real-time learning analytics to continuously monitor the learner's progress and dynamically alter the suggestions. Furthermore, the integration of multimodal educational data (textual, audio, video, physiological and eye-tracking data) might increase the accuracy of learner profile. Future research may also explore the use of XAI to improve the transparency and interpretability of learner predictions and recommendations. Moreover, the blend of RL, generative AI, and LLMs may power intelligent tutoring, conversational learning assistance, and adaptive content development. Finally, further validation of the proposed system across broader, multilingual and cross-cultural educational datasets and its deployment in real-world LMS would further show its scalability, practical application and usefulness in enabling individualized instruction.

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