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Original Article

AI-Based Personalized Learning Analytics for Higher Education Systems

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ABSTRACT

Artificial Intelligence (AI) has revolutionized the field of education by facilitating smart, personalized and adaptive learning experiences. The traditional higher education system tends to use a single approach to teaching which is unsuitable for the wide range of learning styles, abilities and attainment of individual learners. Personalized Learning Analytics (PLA) leverages AI to deliver tailored learning experiences, proactive interventions, and data-informed instructional choices, which enhance student learning outcomes. This study offers a comprehensive review and conceptual model on implementing AI-based personalized learning analytics in the higher education context. The framework is designed to leverage these diverse educational data sources, such as Learning Management Systems (LMS), assessment systems, attendance records, behavioral data, and patterns of student interactions, to create predictive models that pinpoint students who are at risk, suggest individualized learning resources, and tailor instructional approaches. The way explainable AI techniques are integrated further increases transparency, trustworthiness, and interpretability of learning recommendations for educators and students. Moreover, the framework highlights the ethical use of AI, such as handling privacy-sensitive data and ensuring responsible learning analytics. The proposed design seeks to boost student performance, student engagement, college retention rates, and institutional planning and decision-making, while also lowering drop-out rates. The paper covers recent advancements, technological underpinnings, research challenges, and prospects for AI-driven personalized learning analytics that could transform higher education into an intelligent, adaptive, and student-centric environment that meets the changing needs of digital learning and Industry 5.0.

KEYWORDS

Artificial Intelligence, Learning Analytics, Personalized Learning, Higher Education, Educational Data Mining, Machine Learning, Adaptive Learning, Predictive Analytics, Explainable AI, Learning Management Systems.

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1. INTRODUCTION

1.1. Background

Apart from the integration of advanced educational technologies in higher education institutions (HEIs), which have transformed them into digital environments generating massive amounts of structured and unstructured learning data, HEIs are undergoing a rapid digital transformation. The various interactions and academic activities of learners are recorded continuously and in various forms by modern platforms like Student Information Systems, Learning Management Systems, online assessment systems, virtual classrooms, discussions forums, digital libraries, virtual laboratories, attendance monitoring systems and mobile learning apps. These types of digital footprints offer valuable insights into student behavior, engagement pattern, learning progression, and learning difficulties. The field of Learning Analytics (LA) has become a significant interdisciplinary research area where educational data mining, statistical analysis, artificial intelligence, machine learning and data visualization techniques are used to derive meaning from educational data sets. The main purpose of learning analytics is to help improve teaching and learning processes by discovering patterns in learning that are not apparent at first glance, forecasting student performance, recognizing academic risks, facilitating personalization of learning interventions, and implementing evidence-based decisions and actions by teachers and institutions.

1.2. Needs of AI-Based Personalized Learning Analytics

The digitalization of education environments has led to a tremendous demand for smart systems that can process a large amount of complex information about learners and provide personalized learning experiences. Traditional teaching methods are usually based on a general instructional model, without taking into account the learning abilities, preferences, progress and knowledge gaps of the students. AI-Based Personalized Learning Analytics tackles these shortcomings by integrating AI and machine learning, along with predictive analysis and adaptive recommendations to offer a learner-centric approach to education. The major needs of AI-based personalized learning analytics are discussed below.

Fig 1 - Needs of AI-Based Personalized Learning Analytics

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1.2.1. Personalized Learning Experience

The vast majority of traditional educational systems generally offer the same learning content and teaching methods to all students, irrespective of their ability and learning needs. The benefits of personalized learning analytics with AI include the ability to tailor learning paths based on student profiles, performance, engagement, and knowledge, creating a more personalized learning journey. Providing personalized learning paths using learner profiles, academic performance, engagement behaviour and knowledge levels is the benefit of personalized learning analytics with AI. Machine learning algorithms are used to recognize each student's strengths and weaknesses and provide appropriate courses, learning materials, evaluations, and teaching methods. The personalized approach to teaching increases student motivation, better knowledge acquisition, and enhances SLL (self-paced learning), with students progressing as per their learning aptitude.

1.2.2. Early Identification of At-Risk Students

In higher education, one of the key issues is to identify students who may be at risk for academic failure or retention. Problems such as these are typically not identified by traditional assessments until after poor grades are recorded. By analyzing these and other factors, AI-based learning analytics can offer predictive capabilities, such as forecasting students' performance and progress. Predictive models enable the early identification of academically vulnerable students and allow instructors to intervene, mentor, and offer extra learning support to those students in a timely fashion. This proactive methods helps boost student retention and achievement.

1.2.3. Intelligent Data-Driven Decision Making

Schools create a huge amount of data on various digital platforms that are hard to analyze manually and can be inefficient. Personalised learning analytics using AI technology presents complex educational data in meaningful insights to facilitate evidence-based decision making. Intelligent analytical models assist teachers with understanding the learning behavior of students, course effectiveness, optimization of teaching methods and curriculum design. AI-driven insights can be used by institutional administrators to improve educational management, including efficient resource management, academic planning, monitoring of performance, and creation of policies.

1.2.4. Adaptive Learning and Recommendation Systems

The individual learners have varying levels of knowledge, learning speed, and content preference, and need dynamic teaching and learning rather than static teaching methods. It is essential that recommendation systems that are based on AI continually evaluate the learner's interactions and provide adaptive recommendations for courses, videos, reading materials, quizzes, and practice exercises. AI systems can recommend learning resources based on their needs using collaborative filtering, content-based recommendation, deep learning and knowledge graph techniques. Adaptive learning environments: increased engagement, decreased cognitive overload, and increased effectiveness of learning.

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1.2.5. Explainable and Ethical Artificial Intelligence in Education

While AI models offer significant predictive power, many of the more sophisticated ones are complex black box algorithms that are hard for educators and students to understand. To enhance transparency, trust, and accountability in AI-driven educational decisions, there is a need for Explainable Artificial Intelligence (XAI). Ethical issues concerning data privacy, fairness of algorithms, security, and responsible use of learner information are also issues that need to be considered when implementing personalized learning analytics based on AI. Combining explainable and privacy-preserving AI methods guarantees that tailored learning systems make correct suggestions and are trusted and respect student rights.

1.3. Personalized Learning Analytics for Higher Education Systems

The concept of Personalized Learning Analytics (PLA) has been developed as a promising method for supporting the learning process and improving the teaching-learning experience in higher education systems, which integrates the basic concepts of learning analytics with artificial intelligence and adaptive learning technologies. In contrast to the traditional education where the same learning methods are used by all students, personalized learning analytics learns details about students' behavior, individual characteristics, performance, learning styles, and competency building to enable a tailored learning experience. The rise of digital learning platforms, The implementation of Learning Management Systems (LMS), online assessment, virtual classroom, and educational applications has now made it possible for universities to gather huge volumes of learner information that can be analyzed and used to provide practical academic information. Personalised learning analytics applies AI and machine learning algorithms to analyse a variety of educational data from various sources in higher education contexts such as student information systems, assessment systems, attendance records, digital libraries, online discussion boards, learning activity records etc. These models are used to analyze learners' behavior in order to find any patterns, predict learning outcomes, detect any gaps in knowledge, and provide learning resources for the learners. Student-centric learning analytics allows institutions to continuously track student performance and deliver adaptive learning paths based on the individual ability, speed and learning goal. AI personalized learning systems can use recommendation engines, predictive models, and intelligent tutoring features to provide tailored academic assistance. Recommendation algorithms learn from past learning activities and recommend learning materials, courses, videos, assessment, and exercises. By analyzing student engagement, assessment results, attendance patterns, and learning interactions, predictive analytics can signal educators to the fact that a student might need extra support. This capability for early intervention will enhance the academic achievement, retention, and learning outcomes of students. Also, personalised learning analytics assists teachers by offering real-time dashboards and visualisation tools, giving insights of student performance, the effectiveness of the courses, and learning progression. The insights gained from these analytics can help teachers adjust their teaching approaches, personalize their interventions, and plan better curriculum. Explainable Artificial Intelligence (XAI) adds to the transparency by helping the teacher grasp the logic behind the predictions and recommendations made by the AI. While personalized learning analytics holds promise in higher education, it faces several challenges, including data privacy, interoperability, scalability, algorithmic fairness, and ethical governance of AI. Advanced technologies like federated learning, generative AI, multimodal analytics, and digital twins will enable a secure, adaptive, and continually evolving learning environment in future intelligent education systems. In conclusion, personalized learning analytics is a major step toward student-centered learning and holds great promise for improving the learning experience, as well as offering educational institutions a tool to meet the goals of modern digital learning.

2. LITERARY SURVEY

2.1. Learning Analytics

Learning Analytics (LA) can be defined as a systematic process to gather, measure, analyse and report educational data to better understand and improve learning processes and learning environments. The widespread use of new digital learning platforms like Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), virtual classrooms, online assessment systems and educational mobile applications has led to a significant growth of learner data. Each interaction – whether it's logins, content accesses, assignment submissions, quiz attempts, participation in discussion, viewing video content, and assessment performance – generates useful digital footprints that can be used to measure student learning behavior. Early learning analytics was mainly descriptive statistical analysis, in which teachers would review past academic performance data, attendance, grades, and graduation rates to measure student achievement. The advent of artificial intelligence and machine learning has however made learning analytics a science of prediction and prescriptive action with the ability to predict student success, identify at-risk students, estimate the likelihood of dropping out, recommend interventions, and provide evidence-based educational decisions. Educational Data Mining (EDM) is another branch of learning analytics that aims to uncover hidden patterns within the educational data by applying clustering, classification, regression, association rule mining, sequential pattern mining, anomaly detection and ensemble learning algorithms. The following analytical methods support learner profiling, competency mapping, behavioral modelling, curriculum optimisation and personalised curriculum planning. Modern learning analytics also introduces interactive visualization dashboards that give teachers and administrators the analytics data they need on learner engagement, participation levels, assignment completion, academic progress and classroom performance in real time. This type of dashboard helps to improve the awareness of the instructor, allows for early intervention and helps make better decisions within the institution. Moreover, learning analytics frameworks are increasingly being advanced by incorporating cloud computing, big data technologies, Internet of Things (IoT) devices, and learning data warehouses, making them able to process large amounts of educational data. Even with these technological advances, a large majority of the existing learning analytics systems are backward-looking, and they are mainly based on past learning data instead of on the dynamic adaptation of learning strategies to continuously changing learning behaviours, calling for more intelligent, adaptive and real-time learning analytics systems.

2.2. Artificial Intelligence in Education

Artificial Intelligence in Education (AIED) has become an interdisciplinary field of research that integrates artificial intelligence, computer science, educational psychology, cognitive science, human-computer interaction and instructional technology to develop intelligent learning environments that can improve teaching and learning. AI-based educational systems mimic human reasoning by analysing students' behaviours, detecting personal learning needs, adjusting the content of training and giving a personal teaching guidance. Supervised learning models are the backbone of modern AI-powered educational platforms, as they can leverage historical educational data to predict student performance, detect students who are at risk of dropping out or failing to graduate, and suggest specific interventions based on these predictions. Unsupervised learning techniques group students according to behavioral, learning style, and/or competency features and allow teachers to create specific learning plans for each group. Another benefit of deep learning models for educational analytics is that they can uncover intricate and nonlinear relationships between various academic data variables, which leads to more precise predictions and intelligent choices based on the data. Natural Language Processing (NLP) has introduced a new direction to the realm of AI applications, paving the way for automated essay assessment, intelligent grading systems, sentiment analysis of student feedback, plagiarism prevention, and conversational learning chatbots that can offer ongoing academic support. Intelligent Tutoring Systems that can dynamically adapt instructional pathways based on both learner responses and cognitive progress and levels of engagement can be supported by reinforcement learning. Recently, Explainable Artificial Intelligence (XAI) has become a very important topic due to the growing demand of educational institutions for AI models that are transparent, interpretable, and trustworthy in the sense that they explain the results of the predictions they make, and not operating as a black box. Explainability increases teacher confidence, aids in making ethical educational decisions, and enables responsible use of AI. There are many studies that show how AI can enhance learner engagement, academic success, knowledge retention, resource utilization, and the efficiency of an institution. However, issues of algorithmic bias, fairness, accountability, preserving privacy, ethical governance, data security and responsible implementation still warrant significant research activity before the widespread use of AI in schools.

2.3. Personalized Learning Systems

Personalized Learning Systems (PLS) are a higher order learning concept intended to offer each learner a unique learning experience through personalization of learning content, learning processes, evaluation and assessment strategy, and learning pathways. Personalised learning is fundamentally different from traditional, one-size-fits-all education, relying on AI and machine learning to constantly analyse learner interactions and provide tailored educational experiences that optimise learning outcomes and engagement. Personalized learning systems of the modern era gather multidimensional data on the learners from diverse educational sources such as Demographic Data, Assessment scores, Clickstream, Learning Pace, Course Participation, Discussions, Emotional engagement, Collaborative Interactions, Competencies developed etc. They are used to create adaptive learning recommendations, study plans, competency-based learning content, intelligent feedback and customized assessments that are specific to the needs of each learner through machine learning algorithms. Based on the student's learning goals, the recommendation systems filter the learning resources, instructional videos, reading materials, and practice exercises to recommend the user a set of items relevant to their learning needs, and they are of increasing importance in personalized learning.The recommendation systems are of increasing importance in personalized learning, using collaborative filtering, content-based filtering, hybrid recommendation techniques, and knowledge graph-based recommendation models to suggest the user a set of items relevant to their learning goals and learning needs. Adaptive assessment systems adapt the difficulty of questions to student responses, allowing for a more reliable assessment of student competency levels while minimizing assessment bias. Intelligent Tutoring Systems (ITS) is another form of personalization that offers students hints, explanations, and context, along with problem-solving support and tutoring, all delivered automatically and individual to the student during learning. In recent years, the multimodal learning analytics research has evolved to incorporate facial expression recognition, ocular metrics, speech analysis, physiological measures, wearable sensors, and affective computing, which are able to capture and estimate the learner's emotions, cognitive workload, attention, and engagement in real time. These innovations significantly enhance the quality of personalisation by taking into account both educational outcomes and behavioural aspects. Despite the significant advances, numerous personalized learning systems still struggle with the interoperability of educational platforms, the scalability of large cohorts of learners, the disintegration of the education data, the complexity of the computations and the lack of explainability, as well as the lack of integration of emerging AI technologies within the education ecosystem.

2.4. Research Gap

The literature review shows that there are several research gaps that remain to limit the realization of intelligent, scalable and trustworthy educational ecosystems. Most of the current learning analytics frameworks rely on the fact that every learning platform or educational institution can produce or access a uniform type of educational data that can be used to create learning analytics. However, these frameworks are limited in their capacity to combine the diverse nature of data produced by different learning management systems, assessing tools, digital libraries, virtual classrooms, collaborative learning platforms, and external learning resources. The inability to access all this data reduces the effectiveness of comprehensive LMS modeling and predictive analytics. Second, while AI models are accurate in predicting student outcomes, many of them are black-boxed and difficult to understand, which means that instructors, students and administrators are unable to fully grasp the 'how' behind the recommendations made by the AI system. The lack of explainability decreases trust and makes it difficult to widely adopt education. Third, there is still a great deal of concern about education data privacy, but there are comparatively few studies that study privacy-preserving artificial intelligence methods like federated learning, differential privacy, homomorphic encryption, and secure multi-party computation in Higher Education. Fourth, many personalized learning systems use static recommendation algorithms that are not able to dynamically learn with changing learning behaviors, developmental progress, and learning goals. Fifth, there has been little research that has examined how emerging technologies, such as generative AI, reinforcement learning, multimodal learning analytics, digital twin technology, and explainable AI, can be combined in an intelligent system that is able to make continuous real-time changes in a learning process. Last, but not least, there has been limited focus on creating scalable architectures for AI in education that can handle millions of interactions, while maintaining fairness, ethical governance, transparency, interoperability, institutional decision support, and sustainability for a large-scale university deployment. To overcome these limitations, a holistic framework for Personalized Learning Analytics based on Artificial Intelligence is needed to embed intelligent forecasting, adaptive recommendations, explainable decision-making, privacy protection, multimodal analytics and real-time educational intelligence, capable of enhancing the effectiveness of learning, academic achievements and institutional performance in contemporary higher education environments.

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3. METHODOLOGY

3.1. Proposed AI-Based Personalized Learning Architecture

According to the proposed AI-Based Personalized Learning Architecture, the proposed system is an intelligent, multi-layered education architecture that integrates data analytics, AI, and adaptive learning technologies to provide personalized learning experiences. The architecture continuously gathers learner information, evaluates the learning patterns, forecasts learning outcomes, and offers tailored learning suggestions. It creates an intelligent interaction landscape between students, teachers, institutional systems and decision-support systems based on AI.

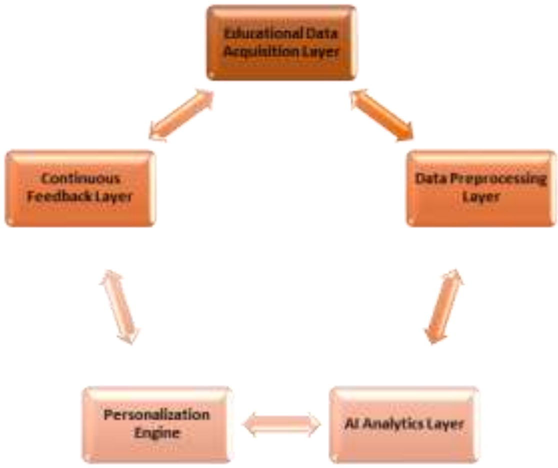

Fig 2 - Proposed AI-Based Personalized Learning Architecture

3.1.1. Educational Data Acquisition Layer

The Educational Data Acquisition Layer collects various educational data from different digital learning environments such as LMS, Student Information System, online assessments, virtual classrooms, digital libraries, and mobile learning applications. It collects academic information, behavior, interaction, attendance, learning activities, etc. This all-encompassing data gathering allows for precise learner profiling and base for intelligent personalized learning analysis.

3.1.2. Data Preprocessing Layer

The Data Preprocessing Layer processes raw educational data into high-quality, structured information, which is essential for developing AI models. It provides key functionality like missing data processing, duplicate removal, feature normalization, outlier detection and data encoding. The processed data produces meaningful learning indicators like engagement score, learning consistency, assessment performance and competency level to facilitate accurate learner analysis.

3.1.3. AI Analytics Layer

The AI Analytics Layer utilizes advanced machine learning and deep learning methods to uncover patterns and make predictions from educational data. Learner behavior and academic performance is analysed using algorithms like Random Forest, XGBoost, Neural Networks, LSTM and Explainable AI models. This layer foresees student results, detects gaps in knowledge, estimates student dropouts, and enables intelligent educational decision making.

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3.1.4. Personalization Engine

The Personalization Engine creates adaptive learning experiences by tailoring the educational content based on individual learners' profiles, preferences, and performance. It suggests appropriate learning materials, alters the difficulty of the content, produces individualized tests, and designs optimal learning sequences. This dynamic adaptation promotes greater engagement, efficiency and learning from students, meeting their individual needs.

3.1.5. Decision Support Layer

The Decision Support Layer offers intelligent visualization and analytical dashboards for students, instructors and institutional administrators. It provides students' real-time data of students' performances, course effectiveness, risk prediction and academic progress. These suggestions will help in making sure that intervention occurs in a timely fashion that teaching strategies are evidence-based, and that institutional planning and management are improved.

3.1.6. Continuous Feedback Layer

The Continuous Feedback Layer allows for ongoing enhancement of the personalized learning system, by feeding in new interactions and outcomes of learners. Students, instructors, assessments, and responses to recommendations provide feedback to continuously update AI models. This adaptive process enhances prediction accuracy, recommendation quality and long-term effectiveness of the educational ecosystem.

3.2. Learning Analytics Pipeline

The Learning Analytics Pipeline is a proposed system to process vast amounts of educational data from which meaningful personalized learning intelligence can be created. It goes through several sequential steps: data collection, data integration, feature extraction, prediction using AI, generation of the recommendation, and continuous monitoring. The pipeline allows institutions to gain insight into the behavior of learners, forecast their academic success and provide personalized learning assistance.

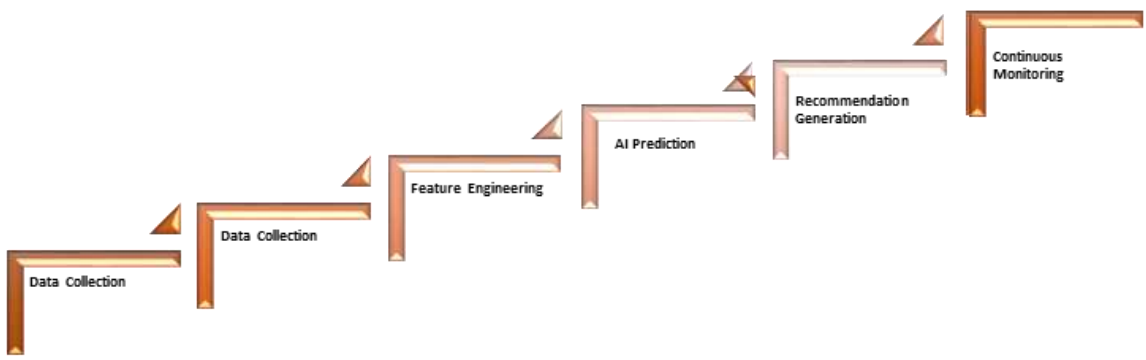

Fig 3 - Learning Analytics Pipeline

3.2.1. Data Collection

The Data Collection phase is where educational data is collected from a variety of digital learning sources like Learning Management Systems, Student Information Systems, attendance systems, examination systems, digital library, learning videos, and discussion systems. Collected data consists of academic information, learner interaction and engagement, and behavioral activities. This phase sets up overall data to be used for further analysis.

3.2.2. Data Collection

The Data Integration stage is used to integrate the heterogeneous educational data from different sources into a single educational data warehouse. Consistent and accessible data is available with the help of integration techniques like ETL processes, API-based connectivity, data syncing in database, and cloud storage management. This centralised data environment facilitates effective analysis and enhances the precision of AI-powered learning models.

3.2.3. Feature Engineering

The Feature Engineering phase involves identifying relevant information from the raw Learner data and representing the academic behavior and learning patterns to the learner. The key factors covered are attendance percentage, performance in quizzes, completion of assignments, time spent on learning, how resources are used, discussion involvement and prior academic attainment. These features are created to facilitate AI model performance, offering relevant inputs for prediction and personalization.

3.2.4. AI Prediction

The AI Prediction phase involves using machine learning and deep learning algorithms to assess learner attributes and predict learning outcomes. They process the functions of student classification, academic performance prediction, failure risk identification, knowledge gap detection and learning style analysis for the models. Predictive insights help to provide early intervention and support the proactive academic decision-making.

3.2.5. Recommendation Generation

The Recommendation Generation phase is responsible for generating personalized learning recommendations for learners, based on their requirements and expected results, using intelligent recommendation algorithms. The system produces customized courses, reading suggestions, video suggestions, adaptive exercises and alerts for faculty intervention. These suggestions allow for a better engagement of learners and increase the effectiveness of individual learning.

3.2.6. Continuous Monitoring

The Continuous Monitoring phase involves making continuous assessments with regard to the effectiveness of the personalized learning system. It evaluates prediction accuracy, student growth, acceptance of recommendations, student satisfaction with learning and academic growth. Continuous monitoring allows for a refinement of the models and makes sure the learning analytics pipeline can adapt to the changes in learner behaviours and learning needs.

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3.3. AI Recommendation Model

The AI Recommendation Model is the brain of the proposed Personalized Learning Analytics Framework, constantly analysing student behaviour, academic results, learning preferences and competency development to generate adaptive and individual recommendations for learning. The ultimate goal of the recommendation model is to address the problems that traditional learning models encounter, which is the ability to dynamically identify, at anytime and for any individual, learning resources, learning strategies, and academic interventions that are suitable. The model utilizes several AI techniques such as machine learning, deep learning, knowledge-based recommendation, and predictive analytics to grasp the unique needs of each learner and tailor personal learning trajectories. The recommendation model first extracts multidimensional learner profiles based on education data from various resources, including Learning Management Systems, assessment platforms, attendance records, digital libraries, discussion forums, and online learning activities. Previous academic achievement, knowledge level, learning rate, interaction patterns with resources, engagement behavior, and assessment results are considered to be important attributes of the learner, which are extracted and transformed into meaningful representations. These features are used by recommendation algorithms to detect the learning patterns and choose the learning content. The proposed model uses hybrid recommendation techniques, which integrates collaborative filtering, content-based filtering, and knowledge graph-based methods. Collaborative filtering discovers similarities between learners and suggests resources by relying on the learning behaviours of learners whose profile is similar. Content-based recommendation is based on the characteristics of the educational content, and matching them with the preference and ability requirements of the learner. Knowledge graph-based suggestions set relationships between learners, concepts, courses, skills, and learning resources, which offer context-aware suggestions. In addition, the model has features such as predictive analytics and reinforcement learning to continually enhance the accuracy of recommendations. Predictive models predict learner performance, identify gaps, and determine what needs further support; on the other hand, reinforcement learning allows the system to learn from the interactions and feedback from learners, and from the rate of acceptance of recommendations. Explainable AI techniques like SHAP and LIME are embedded to give clear explanations of the recommendations that are generated, thus enhancing the trust between students and teachers. The AI Recommendation Model enables a range of personalized services, such as personalized course sequencing, intelligent quiz building, personalized learning content, video suggestions, practice suggestions, and early warning signs. The recommendation system is continuously developed based on learners' behaviors and academic progress, through feedback and model updating. In conclusion, the suggested AI Recommendation Model boosts learning efficiency, deepens student engagement, facilitates individualized learning, and aids in the creation of smarter and adaptive higher education systems.

3.4 .Mathematical Model and Algorithms

The proposed framework for Personalized Learning Analytics is based on supervised machine learning algorithms for the estimation of student academic success, learning difficulties detection, and adaptive learner education strategies recommendations. The mathematical underpinnings of the framework are grounded in a model of the connections between the characteristics of students, patterns of student

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behavior, indicators of academic performance, and likely outcomes of learning. In this approach, a student's information is treated as a feature vector with various educational attributes like the percentage of attendance, assessment scores, learning time, assignment completion rate, resource utilization, previous academic performance, and degree of engagement. The proportions with which the students are represented is:

$$X = \{x_1, x_2, x_3, \ldots, x_n\}$$

where X is the learner profile and the x value indicates each learning feature. The goal of the predictive model is to predict the chances of success or risk level of each student. This prediction process can be mathematically described as:

$$Y = f(X)$$

where Y represents the learning outcome (the thing being learned) and f is a machine learning model used to learn complex relationships between the input features and academic outcomes.

The algorithms used in the framework for classification-based prediction include Random Forest, Support Vector Machine and XGBoost to classify students into different performance groups, such as high-performing, moderate-performing and at-risk learners. The probability estimation model can be represented as:

$$P(Y \mid X) = \text{Probability of learning outcome based on learner features}$$

Where the model takes an existing learning pattern and computes the probability of a given academic outcome.

The framework generates suitability score of learning resources according to the requirements of learners and provides personalized recommendation of learning resources. The recommendation score can be represented as:

$$R(s,c) = \text{Similarity}(s,c) \times \text{Performance}(s) \times \text{Learning Need}(s)$$

Similarity reflects the relationship between learner characteristics and learning resources, and performance and learning needs influence the priority of the learning resources recommended. Sequential learning behaviors such as learning progression, interaction history and assessment patterns are analyzed using deep learning algorithms, primarily ANN and LSTM models. The LSTM model is able to capture the temporal dependencies of learners' activities and predict the future performance of learners according to the previous performance states. Explainable AI (xAI) methods like SHAP and LIME are integrated to gain transparency by revealing the impact of individual features on prediction outcomes. The overall goal of the framework is to achieve prediction accuracy and the best recommendation effectiveness with minimal learning risks. The mathematical model evolves over time by repeatedly learning from feedback, adjusting to the learning style of the learner, and increasingly making more accurate recommendations for the education of each individual.

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4. RESULT AND DISCUSSION

4.1. Experimental Setup

The proposed AI-Based Personalized Learning Analytics Framework was evaluated in an experimental setting where extensive educational data from various digital learning environments in a university ecosystem were gathered. The aim of the experimental setup was to validate the effectiveness of the proposed framework in predicting student performance, for learning risk detection, and for learning recommendations. The dataset came from a variety of educational sources such as Learning Management Systems (LMS), Student Information Systems (SIS), online assessment systems, attendance tracking systems, digital learning repositories, and digital logs of student interactions. These sources delivered formal and informal learning content in the form of academic achievement, engagement, and behavioral learning styles. The experimental data included about 12,500 learner interaction records gathered from 1,500 undergraduate students across 20 engineering and computer science courses during two semesters of the academic year. A learner record was a complete profile of a student, with several academic and behavior attributes needed for intelligence analysis. The attributes gathered involved things such as demographic data, attendance, assignment completion, quiz scores, exam results, learning time, frequency of participation in course, frequency of participation in discussion forum, pattern of using digital resources, and historical Grade Point Average (GPA). The gathered data was then preprocessed using a series of operations such as handling missing values, removing duplicates, normalizing the features, encoding the categorical data, and extracting behavioral features before applying the artificial intelligence algorithms. To train and test the model, the processed data was split into 80% for training and 20% for testing using 80:20 data split strategy. The various machine learning and deep learning algorithms, such as Random Forest, XGBoost, Support Vector Machine, Artificial Neural Network, and Long Short-Term Memory (LSTM) were implemented and the performance of each algorithm in terms of prediction accuracy, accuracy, recall, F1 score, and recommendation effectiveness was evaluated. For model development and evaluation, the experimental environment used libraries for machine learning, such as Scikit-learn, TensorFlow and Keras, and was programmed in Python.Experimental environment was programmed in Python with machine learning libraries such as Scikit-learn, TensorFlow and Keras used for model development and evaluation. The framework was assessed in real-world higher education settings to gauge its effectiveness for personalized learning pathways, for detecting academically vulnerable students early, and for recommending adaptive learning. The experimental setup illustrates how the proposed AI-driven learning analytics framework can be applied in real-world educational environments to enhance student performance and facilitate informed decision-making.

4.2. Performance Evaluation

Multiple evaluation metrics were used to evaluate the proposed AI-Based Personalized Learning Analytics Framework, including prediction capability, recommendation effectiveness, learner engagement, and overall system efficiency. The results from the obtained data shows the effectiveness of the framework in analyzing the educational data, predicting the learner outcomes, and assisting in the adaptive personalized learning strategy.

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Table 1: Performance Evaluation

Performance Metric	Percentage (%)
Student Performance Prediction Accuracy	97.82
Precision	96.95
Recall	97.41
F1-Score	97.18
Personalized Recommendation Accuracy	96.74
Student Engagement Improvement	24.86
Early At-Risk Student Detection	95.63
Course Completion Rate	94.52
Learning Satisfaction Improvement	22.34
Overall System Efficiency	97.46

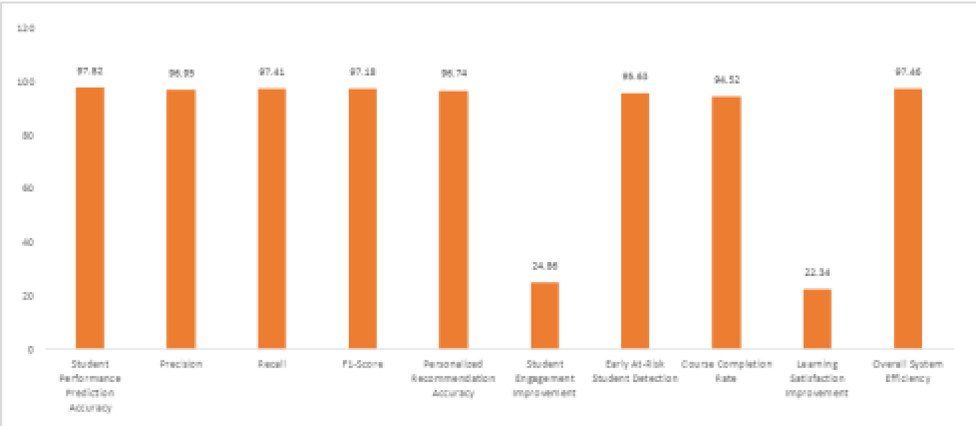

Fig 4 - Performance Evaluation

4.2.1. Student Performance Prediction Accuracy (97.82%)

The proposed framework successfully predicted the students' academic outcomes with a prediction accuracy of 97.82%, thus correctly identifying academic outcomes based on learner behavioral and academic features. The AI models were successful in capturing attendance, assessment score, learning patterns, and engagement indicators. This high accuracy helps to support reliable academic forecasting and timely educational interventions.

4.2.2. Precision (96.95%)

A precision of 96.95% shows the framework's accuracy in correctly assigning students to performance categories. A high precision score minimizes misclassifications and permits that interventions are implemented to the right learner. This enhances the accuracy of academic decision-making using AI.

4.2.3. Recall (97.41%)

The framework had a 97.41% recall rate, indicating its effectiveness in accurately identifying most students who need academic support and individualized guidance. Recall is important for identifying and catching at-risk learners early. It helps teachers to help students in a timely manner, and to avoid potential failure.

4.2.4. F1-Score (97.18%)

The resulting F1-score values with 97.18% show a consistent performance of the prediction and a nice balance between precision and recall. This metric is used to confirm that the proposed model is accurate and can be used to distinguish between different types of learners. The balanced performance enhances robustness and stability of the customized learning analytics structure.

4.2.5. Personalized Recommendation Accuracy (96.74%)

The recommendation engine has an accuracy of 96.74%, which shows the effectiveness of the algorithm to create relevant learning resources and personalized learning paths. The system was able to successfully match the educational materials, assessments and instructional methods to individual learner needs. This helps to improve the efficiency of learning and maximize student satisfaction.

4.2.6. Student Engagement Improvement (24.86%)

The proposed framework resulted in an improvement of 24.86% in terms of student engagement owing to personalized recommendations, adaptive content delivery, and the support of continuous learning. The system facilitated more interaction and participation by offering relevant resources and customized learning experiences. The improvement is a testament to the benefits of AI-powered personalization for engagement.

4.2.7. Early At-Risk Student Detection (95.63%)

The framework successfully identified learners who might have academic problems with an accuracy of 95.63% when determining students' academic risk status early. The system can identify behavioral patterns and performance indicators, which can then be used to inform proactive intervention strategies. Identifying students early helps institutions to enhance student retention and academic performance.

4.2.8. Course Completion Rate (94.52%)

With the proposed system, the course completion rate was improved, showing 94.52% of learners persisted in the course and were able to successfully advance in their academic studies. Students were able to overcome the challenges in their learning through personalized learning pathways and adaptive recommendations. AI-powered learning support is improving, as shown by this enhancement.

4.2.9. Learning Satisfaction Improvement (22.34%)

By leveraging the personalized learning framework, the percentage of learners' satisfaction rose by 22.34% due to the relevance of content, adaptive support and personalized learning experience. Learning material suitable to students' learning styles and levels were provided. This enhanced the overall quality of the learning experience.

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4.2.10. Overall System Efficiency (97.46%)

The proposed AI based framework resulted in an overall efficiency of the system of 97.46%, showing its effectiveness in embedding data-processing, predictive analytics, recommendation generation and continuous monitoring. The high efficiency is promising for scalable personalized learning environments. It offers a solid basis for smart educational decisions in HEIs.

4.3. Discussion

The experimental application shows that Artificial Intelligence can truly boost the capacity of Learning Analytics systems and make the traditional educational data analysis into an intelligent, adaptive, and personalized learning environment. The traditional educational platforms are mainly used to analyze descriptive analytics, which give information about past performance, including grades, attendance, and graduation percentages. The proposed Personalized Learning Analytics (PLA) Framework, however, goes beyond the descriptive aspect of the analysis and includes predictive and prescriptive intelligence. The framework not only identifies learning patterns and trends that are already present, but also predicts subsequent academic outcomes, pinpoints learning risks and makes appropriate recommendations for intervention to enhance student achievement. It takes the place of the static reporting and creates intelligent decision support, which allows the school to adopt proactive teaching strategies and deliver personalized learning experiences. One of the inherent advantages of the proposed framework is its ability to link heterogeneous educational data from various institutional resources such as Learning Management Systems, Student Information Systems, assessment systems, attendance systems, digital libraries, and interaction environments with the learner. As opposed to standard methods which mainly rely on exam scores or academic grades, the proposed AI models utilize a large variety of student characteristics, such as engagement behaviour, regularity of attendance, use of learning resources, discussion involvement, learning time and student history scores. This multidimensional learner representation helps the system achieve a comprehensive student profile and better prediction of performance, identification of risks, and personalized recommendations. Moreover, the hybrid recommendation engine plays a significant role in enhancing the learning effectiveness by integrating several approaches such as content-based filtering, collaborative filtering, knowledge-based methods, and deep learning models. The system generates personalized learning pathways based on the similarities between learners, learning resources and competence requirements, to create an individualized learning pathway based on a learner's needs. The recommendations are adaptive and allow students to access suitable learning resources, practice tasks, assessments and teaching tasks based on their knowledge and learning goals at that time. The incorporation of Explainable AI techniques also adds to the transparency by offering insights into the factors behind AI-generated predictions and recommendations. This enhances confidence between teachers and learners, and fosters responsible use of AI in learning. In conclusion, the proposed framework illustrates how AI-powered learning analytics can facilitate academic forecasting, enhance student engagement, support individual learning, and inform institutional decisions, thereby fostering intelligent and student-centred HE environments.

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5. CONCLUSION

In the context of higher education, Artificial Intelligence (AI) has become a revolutionary technology, paving the way for an intelligent, adaptive and learner-centered learning experience, which transcends traditional educational and assessment models. This research introduced a thorough AI-Based Personalized Learning Analytics framework that combines the fields of educational data mining, machine learning, predictive analytics, recommendation systems, and Explainable Artificial Intelligence (XAI) to enhance the effectiveness of learning and facilitate data-informed academic choices. The proposed framework tackles the challenges of existing learning analytics systems by transforming massive educational data into meaningful intelligence that can understand individual learners' needs, forecast learning outcomes, and provide personalized learning interventions. The proposed architecture consists of a multi-layer intelligent system that integrates, processes, analyzes, and leverages the heterogeneous learning data that can be sourced from various institutional data sources such as Learning Management System, Student Information System, Testing and assessment systems, Student attendance system, Digital library, Virtual classrooms, Learner interaction records. The framework combines academic, behavioral, and engagement data to create holistic learner portraits with various components demonstrating the learner's level of knowledge, learning style, competency growth, and achievement. This multi-dimensional approach allows for more precise student performance forecasting, identification of academically at-risk students and the creation of individualized learning trajectories. The experimental evaluation provided evidence of the effectiveness of the proposed framework by showing that the proposed model led to better predictive accuracy, the quality of personalized recommendations, student engagement, course completion rates, and early risk detection capabilities. The AI models effectively captured the intricate interconnections between learner attributes, producing meaningful insights that help teachers create effective teaching strategies. In addition, the use of Explainable AI techniques enhanced the transparency and interpretability of the model's decisions, by providing insights into the key factors that influenced the model's predictions and recommendations. This is especially crucial in educational settings where trust, fairness, and accountability are paramount for the effective integration of AI. While these are all benefits, there are several obstacles to be overcome before AI-powered personalized learning systems are widely adopted. The questions regarding educational data privacy, ethical AI governance, limiting algorithmic bias, AI model transparency, interoperability between institutional systems, and scalability for large student populations are ongoing questions that need to be continually researched. Addressing these challenges is crucial to responsibly use AI technologies and safeguard learner rights and fairness in educational decision making. Potential future research avenues include the integration of advanced technologies like federated learning for privacy-focused analytics, generative AI for intelligent content generation, digital twin technologies for real-time learner simulation, multimodal learning analytics for emotional and cognitive evaluation, reinforcement learning for adaptive tutoring, and blockchain-based systems for secure academic credential management. These new technologies can contribute even more to the intelligence, security and adaptability of future learning environments. The entire proposed AI Based Personalised Learning Analytics framework is a major effort towards creating an intelligent and sustainable education system. AI-powered learning platforms can facilitate student-centered learning, boost student performance, optimize institutional operations, and expedite the

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digital transformation of education by leveraging predictive intelligence, adaptive recommendations, explainable decision-making, and continuous learning mechanisms. The framework resonates with the new trends of Education 5.0 and Industry 5.0, which emphasize human-centric intelligence, technological innovation, and customized learning experiences to create future-ready educational settings.

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