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Ethical And Privacy-Preserving Framework For AI-Based Personalized Learning Systems

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Abstract

The fast development of digital learning technologies has presented the tremendous opportunity based on the creation of intelligent educational systems that serve the needs of different learners. Conventional online learning systems tend to be based on fixed instructional systems, which do not respond well to the behavior of individual learners, their level of engagement, or their learning rate. Consequently, the need to have data-driven learning models, which are able to offer customized directions and guarantee data ethics as well as data privacy, is growing. The current research introduces a smart learning system, which combines behavioral learning analytics, artificial intelligence, and privacy-saving solutions to improve customer engagement and educational performance. The data in educational formats were gathered through the digital learning platforms and preprocessed using the structured preprocessing techniques such as data cleaning, data normalization, and feature engineering. The following machine learning models were used to study the patterns of interaction between learners and provide adaptive learning advice: collaborative filtering, classification algorithms, and deep learning methods. Privacy-saving approaches (such as federated learning and different privacy mechanisms) were incorporated to provide safe model training and maintain sensitive information about learners. The fairness assessment processes were applied to determine possible biases in model predictions and ensure fair learning contingency among various groups of learners. The behavioral engagement indicators that were used to evaluate the experimental approach included study time, completion rate of modules, and forum interaction, as well as assessment performance. The outcomes indicate that the combination of adaptive learning algorithms and behavioral analytics has a significant positive impact on the level of engagement of learners, the rate of completing the module, and the overall outcomes of academic performance. The quantitative analysis also shows that the engagement behavior of learners and assessment performance are closely related and correlated, which explains the necessity of maintaining the constant interaction of the learner in the digital learning process. On the whole, the results indicate that the given intelligent learning framework can be useful to deliver personalized learning experiences and ensure privacy protection, fairness, and secure data processing in the contemporary digital educational systems.

1. Introduction

Artificial Intelligence (AI) has largely revolutionized the contemporary classroom by facilitating the creation of customized learning systems where the instruction content, learning speed, and approaches to assessment are personalized to meet the needs of specific learners [1]. Personalized learning systems based on AI use powerful computational methods, which include machine learning, deep learning, and data analytics to process high amounts of learner data, such as interaction history, academic history, and behavioral history [2]. These are systems that facilitate adaptive learning processes, intelligent tutoring, and automated recommendation systems that aim at enhancing student engagement and learning [3]. Knowledge tracing models, reinforcement learning algorithms, and collaborative filtering approaches are the most common technologies that have been implemented to improve the accuracy of recommendations and instructional flexibility [4]. Adaptive learning environments and intelligent tutoring systems also show that AI can offer AI-driven feedback and personalized instructions to learners, thus enabling the learning process to be more efficient and responsive [5].

Learning analytics and Educational Data Mining (EDM) insights are a critical ingredient to the effectiveness of AI-based personalized learning systems [6]. The methods are aimed at gathering, examining, and extracting extensive amounts of learning information produced with the use of digital education tools, such as learning management systems, online tests, and interactive learning tools [7]. Learning analytics is concerned with the comprehension and optimization of the learning procedures through the analysis of student interest, conduct, and achievement, whereas educational data mining is concerned with creating computational methods that can reveal obscure patterns in educational data [8]. Classification, clustering, prediction modeling, and sequence analysis are methods that are popular in identifying learning trends, predicting student performance, and identifying possible learning difficulties [9]. Though these data-driven methods offer useful data that enhances decision-making in education and dynamic learning settings, the enormous gathering and dissection of student data also present major privacy issues [10].

The educational systems are becoming more dependent on large amounts of information that includes sensitive data, including academic documentation, behavioral relationships, demographic details, and learning practices [11]. On the one hand, this information helps to personalize a person more correctly and deliver better learning analytics; on the other hand, it provokes a question about the protection of privacy and the use of data responsibly [12]. Unless proper security measures are in place, centralized storage and mass processing of educational data can bring students the threats of unauthorized access, identity theft, profiling, or unintentional disclosure of data [13]. Besides, numerous digital learning platforms do not have transparent systems that explicitly tell students about the way their data are gathered, used, and distributed. [14] Matters of data ownership, informed consent, and long-term data retention have thus turned out to be topical concerns in educational data governance. As a result, the recent studies have highlighted the application of privacy-protective machine learning methods in order to make sure that sensitive educational information is safe in the process of data analysis and model training [15].

Privacy-depriving machine learning has become a viable solution to privacy concerns in educational systems based on AI, which can help tackle the data protection predicament without sacrificing the efficiency of the learned system [16]. Federated learning, differential privacy, secure multi-party computation, and homomorphic encryption are some techniques used to ascertain machine learning models can be trained without direct exposure to sensitive user data [17]. Federated learning enables the decentralized training of models on multiple devices or institutions and so influences the reduction of the use of centralized data storage; differential privacy incorporates controllable noise to datasets or model output with the aim of ensuring that individual data records are never identified [18]. The combination of these methods helps form secure and trustworthy machine learning systems and maintains the performance of the models [19]. Meanwhile, the use of privacy-sensitive methods is consistent with more general attempts to advance ethical AI in education, in which responsible utilization of data, transparency, and accountability are viewed as fundamental to the development of trustful AI-based learning settings [20].

Ethical AI in education also accentuates the need to combat the concerns of algorithmic bias, fairness, and control in AI-based decision-making processes [21]. Models of the AI trained on past data can unknowingly give biased results when the underlying data sets are unbalanced or are disproportionately represented [22]. During education, biased algorithms can affect recommendations, evaluation processes, and learning opportunities in ways that disadvantage certain groups of students [23]. In order to counter these risks, fairness-conscious machine learning schemes, bias detection schemes, and explainable AI schemes have been suggested to enhance transparency and accountability in automated decision-making schemes. Clear regulatory and policy frameworks are needed to make sure that AI is deployed responsibly, advance the protection of data, and provide ethical norms for educational technologies [24]. The latter frameworks also emphasize the importance of robust cybersecurity on the educational platform that uses AI since these systems handle vast amounts of sensitive information and can potentially fall prey to cyber threats, adversarial attacks, and unauthorized access. Ensuring the AI-based learning systems are more secure is thus vital towards ensuring that the information of students is safeguarded, that the systems maintain their integrity, and that learners, educators, and the educational institutions trust the systems [25].

2. Research gap

The existing studies of AI-based personalized learning systems have primarily aimed at the enhancement of the accuracy of recommendations and adaptive learning performance with the method of learning analytics and educational data mining applications. Nonetheless, the aspect of embedding privacy protection, ethical concerns, and security systems in these systems has not received much focus. Most of the current strategies are associated with centralized data collection that enhances the chances of breaching privacy and unauthorized access to sensitive information of students. Besides that, the problem of algorithmic bias and educational AI model fairness is not adequately tackled. A thorough framework uniting privacy-conscious machine learning, fairness-conscious algorithms, and robust security solutions is required to aid in the support of reliable and accountable AI-driven personalized learning settings.

3. Research Methodology

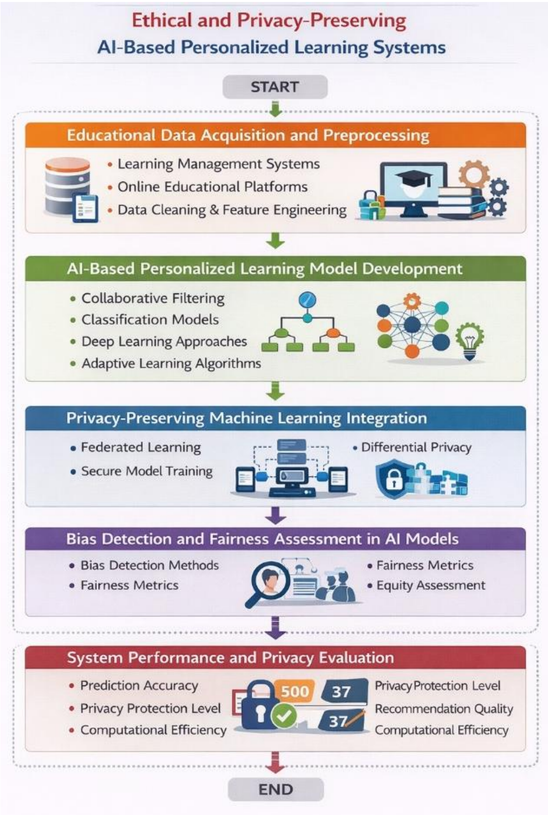

FIGURE 1. Research methodology Flowchart

Educational Data Acquisition and Preprocessing

The acquisition of educational data was performed within the frame of structured online learning environments to receive the overall information about the interactions between learners and their academic achievement. The data sources were mostly based on Learning Management Systems (LMS) and online learning platforms, where learners were exposed to course content, examinations, and group projects [26]. These systems captured different kinds of data created by learners, like interaction logs, assessment scores, completion of modules, duration of time learning activities were done, and time spent in discussion forums. The gathered datasets gave specific information on the behavior and engagement patterns of learners, which became the base input of the future analytical and machine learning steps in the framework of personalized learning.

After the data acquisition phase, a preprocessing system was made as a system to ascertain the quality and reliability of the data. The raw data of the educational systems were analyzed to identify incomplete data, duplicated records, and inconsistent entries that adversely influence the accuracy of the analysis. Data cleaning processes were also done to eliminate noise and resolve formatting errors in the dataset [27]. The missing values were addressed with the help of proper statistical or data imputation methods so that the integrity of the dataset is preserved. This preprocessing step predetermined the fact that the gathered educational data were appropriate to be processed further under the analytical modeling and machine learning application.

The standardization of the variables collected was done after the cleaning process using data normalization and transformation techniques. Educational data usually includes variables of varying scales of measurement, including length of engagement, test scores, and frequency of interaction. Thus, the normalization procedures like min-max scaling and standard score transformation were employed to put all the variables into a similar numerical range. This move reduced the amount of bias in the data and increased the stability and the performance of the machine learning algorithms used in subsequent phases of the research structure.

Lastly, the process of feature engineering was performed to derive significant indicators reflecting the behavior and academic progress of learners. The processed dataset made key features, such as quiz performance, rate of assignment completion, module completion patterns, frequency of interactions, time used on instructional content, and engagement in collaborative activities [28]. These features were extracted features that gave an ordered form of learner attributes and patterns of engagement. The obtained set of features became the leading input in the creation of AI-based personalized learning models and further analysis steps of the given research scheme.

AI-Based Personalized Learning Model Development

The model of the AI-based personalized learning was developed with the help of the preprocessed educational data, which were obtained at the stage of data acquisition and preprocessing. The organized data with patterns of interaction between learners, evaluation, and signs of engagement were the main input in the development of the model. The relevant features that show the behavior of learners, their academic performance, and the course of learning were chosen to form predictive and recommendation models [29]. These capabilities allowed the system to examine individual learning traits and identify patterns used to develop personalized learning recommendations.

The methods of collaborative filtering were used to determine the resemblances between the learners depending on their interaction patterns and performance history. Through the use of historical data on learners, the collaborative filtering strategy allowed the recommendation of the right learning resources to similar behavioral and academic learner profiles [30]. Through this approach, the system was able to propose instructional resources, activities, or learning units that were already shown to be effective to learners possessing similar learning attributes. This produced individual learning recommendations to aid in enhanced engagement and learning results.

Besides collaborative filtering, machine learning models based on classification were used to cluster the learners based on their performance levels, engagement behavior, and learning progress. Labelled data sets were used to train supervised learning algorithms to predict performance of learners and determine any potential gaps in learning [31]. These classification models helped to determine learners with the need to have more instructional support or adaptive feedback. The use of deep learning methods was integrated to identify more complicated relationships in the educational data and enhance the predictive power of the customized learning system.

The model was later implemented with adaptive learning algorithms to change the instructional pathways in response to the estimated learning requirements of individual learners. The algorithms kept on examining the performance of learners, indicators of engagement, and feedback reactions to alter the order and the level of learning content. This dynamic system was able to offer individualized guidance, customized instructional materials, and live learning suggestions through this adaptive mechanism. The personalized learning model was developed through the combination of collaborative filtering, classification models, deep learning methods, and adaptive learning algorithms to help users to enjoy intelligent and data-driven learning experiences.

Privacy-Preserving Machine Learning Integration

It was also made to integrate privacy-saving machine learning methods to make sure sensitive learning information was not compromised during the model training and analytics. As AI-based personalized learning systems were formed on the basis of enormous amounts of data created by the learner, corresponding privacy protection systems were introduced to avoid unauthorized access and possible data leakage [32]. The processed educational data was used in a controlled computing infrastructure in which privacy-protecting protocols were used prior to the implementation of machine learning models. This step made it possible to implement the analytical procedures without disclosing the personal data of learners.

Federated learning emerged as a decentralized model training technique in order to minimize the risks linked with the centralized data storage. In this approach, machine learning models are locally trained on distributed datasets across various learning platforms or institutional settings. Rather than sending the raw learner data to a central server, only the trained model parameters were sent out and processed to update the global learning model [33]. This decentralized system of training reduced to a considerable extent the exposure of sensitive student information and preserved the efficiency of predictive and recommendation models in the personalized learning environment.

Federated learning was also used in conjunction with differential privacy technology to ensure additional protection of data in the process of training and evaluation of the model. Statistically noisy data sets or model outputs were injected to prevent single data record observability in the system. The use of differential privacy was to guarantee that the analysis outcomes of the machine learning models did not divulge confidential information of named learners [34]. This strategy enabled the system to generate meaningful patterns out of the educational data and retain the anonymity of a single user.

Lastly, safe model training processes were enforced to uphold the integrity and confidentiality of the machine learning process. To ensure the security of the transmission of data and model updates in distributed training, encryption mechanisms and secure computation protocols were added. The mechanisms of access control were also used to control the interactions that were not authorized by the system. All these privacy-preserving measures enabled the creation of a safe AI-driven individualized learning environment in which data-driven analysis can be effectively conducted without compromising learner privacy and the security of educational information.

Bias Detection and Fairness Assessment in AI Models

Bias identification and equity measurement were performed to make sure that the personalized learning models based on AI resulted in fair and unbiased results for the diverse learners. Bias in the form of historical educational data imbalance or representational imbalance can cause unwanted bias in the predicting and recommending process since machine learning models are trained on past educational data [35]. To overcome this problem, the trained models were analytically evaluated to find out any tendencies of biased decision-making based on the learner features like performance levels, engagement tendencies, or demographic features. This critique was to confirm the personalized learning system offered equitable suggestions and learning to all learners.

Detection of bias was adopted to assess the existence of disproportionate results of the predictive models across various learning groups of learners. The statistical analysis methods and algorithm-based auditing processes were used to investigate the differences in accuracy of prediction, frequency of recommendations, and frequency of learning support in various classes of learners. From the comparison of the model outputs across different segments of learners, possible bias in the training data or behavior of the model was determined [36]. These processes allowed finding the patterns where the model can be biased towards or against a group of learners without the intention behind it.

After the bias detection phase, the fairness metrics were used to measure the amount of fairness that exists in the machine learning models. The performance of the AI system among various groups of learners was measured by the metrics of group fairness indicators, predictability measures, and equality of recommendation opportunities [37]. The evaluation procedure guaranteed that the machine learning algorithms generated equal results and retained the accuracy of prediction and recommendation efficacy. The use of the fairness measure provided objective indicators through which the ethical performance of the personalized learning framework was evaluated.

Lastly, the evaluation of equity was done to guarantee that the AI-based learning system facilitated inclusive and equal education. The evaluation of the system outputs was conducted by ensuring that learners who showed various learning behaviors, engagement levels, and performance patterns were provided with the right instructional recommendations and adaptive support. In the case where possible bias was found, a change of the model parameters or training processes was done to enhance fairness. The fairness assessment process helped in the development of an accountable AI-managed learning system that facilitates equal access to education materials without compromising credible and functional personalized learning suggestions.

System Performance and Privacy Evaluation

The system performance and privacy evaluation phase was done to evaluate the effectiveness, reliability, and privacy protection ability of the proposed AI personalized learning framework. Once the personalized learning models, privacy-saving mechanisms, and fairness evaluation processes were incorporated into the system, the entire system was tested in a controlled experimental setting [38]. The system functionality was tested using the processed educational data that produced adaptive learning recommendations and predictive insights. Several measurement parameters were established to evaluate the model performance and to determine the fact that the system was in balance between personalization efficiency and the protection of data privacy.

The performance of the machine learning models in predicting the performance patterns of the learners and suggesting suitable learning resources was determined by evaluating the accuracy of the prediction. Validation datasets were used to test the trained models to determine how the models predicted performance against the actual learner performance records. Some of the standard evaluation metrics, like accuracy, precision, recall, and model reliability, were evaluated to determine the predictive ability of the system. These measures will give objective data on the capability of the AI model to accurately estimate the needs of a learner and guide individual instructions.

Besides the level of prediction, the level of privacy protection was also evaluated to ensure that the privacy-preserving measures that have been introduced are effective. The federated learning and differential privacy were analyzed to guarantee that the confidential data of learners were not directly revealed through the process of training and testing models [39]. The indicators of privacy risks and the situation of a possible leakage of data were examined to ensure that the system was accompanied by proper data management practices. The assessment was able to explain if the use of privacy-protecting strategies effectively safeguarded sensitive learning data without a substantial impact on the model performance.

Lastly, the quality of recommendations and the efficiency of computations were investigated in order to find out the practical applicability of the proposed system. The applicability and usefulness of the suggested learning materials were considered according to the patterns of engagement of learners and their learning outcomes. Also, the metrics of computational efficiency were determined, including processing time, the time taken to train the model, and the scalability of the system to evaluate the viability of the framework operation. The overall analysis of the system performance, privacy protection, recommendation effectiveness, and computational efficiency offered a full evaluation of the proposed AI-based personalized learning system [40].

4. Result and discussions

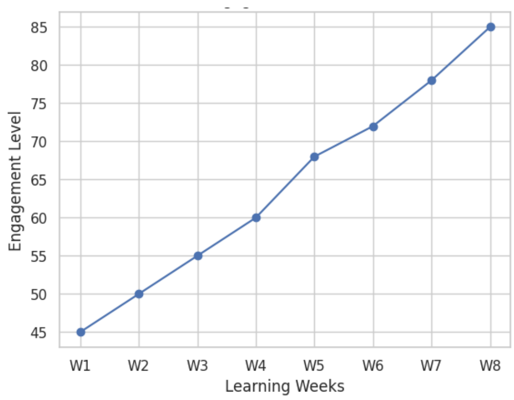

Figure 2: Learner Engagement Trend Across Learning Weeks

The figure represents the evolution of levels of engagement of learners during a learning process that is eight weeks long. The horizontal axis is the learning timeline split into weekly increments (W1-W8), whereas the vertical axis is the level of engagement that was recorded among learners who interacted with the digital learning environment. The values show that the engagement level is increasing steadily over time, starting with about 45, which starts increasing to about 85 in the first and eighth weeks, respectively. This positive trend indicates that learners became increasingly more active in the learning system over the course of time as the instructional activities and adaptive learning processes kept being carried out.

The levels of engagement during the first stage of the learning cycle are on a relatively medium scale, with the values rising steadily between weeks one and four. The trend is one that indicates the initial phase of interaction as learners are becoming acquainted with the digital learning experience, learning content, and the interface of the system. This is the stage when learners usually look into course materials, have an introductory course in learning modules, and start working with assessments and multimedia. The progressive and incremental increase in the levels of engagement, starting with 45-60, suggests that the participation tends to increase progressively as the learners get used to the established learning environment and feel more at ease using the platform.

There is a significant boost in engagement between weeks four and six, with higher rates of engagement recorded between approximately 60 and 72. This stage shows increased engagement of the learner and long-term engagement with the learning process. With further advances in instructional modules, the adaptive learning suggestions and personal feedback systems are likely to promote greater involvement in learning activities. The augmented activity level at this phase signifies that the learners are putting more hours into learning content, accomplishing learning exercises, and using multiple elements of the learning mechanism, like quizzes, discussions, and multimedia teaching materials.

The last stage is the one that takes place between week six and eight and shows the highest engagements, with a peak of approximately 85 at the eighth week. This trend is an indication that the learners are in a mature interaction process whereby consistent interaction and no interruption of the interaction are observed. This type of behavior indicates successful adjustment to the learning setting, higher motivation, and a strong desire to complete the instructional tasks. The gradual increase in the number of interactions throughout the learning process shows the success of the data-driven learning support systems and adaptive teaching methods in keeping the learner interested and ensuring constant interaction within the education platform.

Table 1. Learner Engagement Metrics Across Learning Activities

Learner	Study Time (min)	Modules Completed	Forum Posts	Quiz Score (%)
L1	110	5	4	75
L2	140	7	6	82
L3	130	6	5	78
L4	160	8	7	90
L5	100	4	3	70
L6	150	7	6	88

The table will be a summary of the important indicators of behavioral engagement of learners using the digital learning environment. Patterns in learning behavior were measured using metrics like study time, modules completed, forum participation, and performance on quizzes. It can be observed that the longer learners remain engaged with the learning materials, the higher the module completion rates and quiz scores. For indicators L4 and L6, as an example, the learners have registered greater values in terms of engagement. Conversely, reduced time of study is associated with less involvement and performance. These trends suggest that continuous exposure to the instructional materials has a positive impact on the engagement of the learners, their knowledge acquisition, and their academic achievements in the adaptive learning settings.

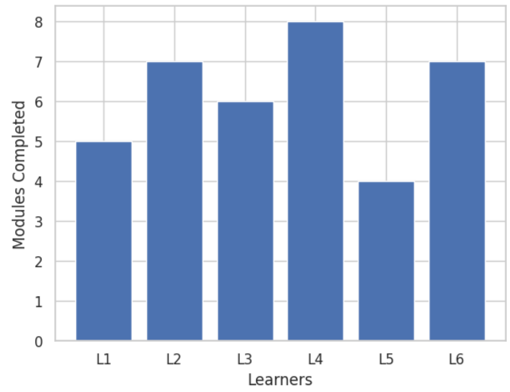

Figure 3. Learner Module Completion Distribution

The figure demonstrates the number of instruction modules accomplished by individual learners in the digital learning environment. The horizontal axis indicates the various learners denoted by L1 through L6, whereas the vertical axis indicates the number of modules taken by each learner in the learning period under observation. It has values displaying considerable differences in the completion levels with four to eight modules. Such distribution creates an emphasis on the disparities of the learning progress between the participants, as it emphasizes the levels of engagement, speed of learning, and patterns of interaction that occur within the system.

On the first level of observation, L1, L2, and L3 learners exhibit moderate behavior in terms of completion of modules with their completion values of five, seven, and six modules, respectively. Such learners seem to have stable development by using the instructional resources but engage constantly with the learning platform. The behavior of such patterns is a sign of equal use of educational materials and implies that these students are actively pursuing the sequence of structured learning that the given platform offers. This is reflected in the behavior pattern, where a consistent learning process is observed as learners progressively move through course materials without major interruptions or abnormalities.

A more advanced scale of instructional development is realized in the case of learner L4, who had the greatest module completion measure of eight modules. This outcome shows that there is high interaction with learning materials and the content consumption rate is higher than among the other participants. Students of this level of completion generally show a steady engagement with the learning materials, a prompt accomplishment of learning processes, and effective navigation of learning modules. When the module completion rates are high, it is usually linked to high motivation and successful adaptation to the digital learning environment, which has a positive impact on the knowledge acquisition and continuity of learning.

Conversely, learner L5 has the lowest completion value of four modules, which means that he/she makes a relatively slow advancement through the instructional material. Such a trend indicates reduced perception, slower learning, or potential learning difficulties, which hinder the learner's progress through the course materials. These differences in module completion can provide useful feedback to adaptive learning systems, enabling the detection of learners who require additional instructional support or individualized advice and recommendations. Generally, the observed diversity in the patterns of module completion is insightful with regard to the issue of learner behavior and the significance of adaptive instructional strategies in meeting the diverse learning needs of learners in the digital learning setting.

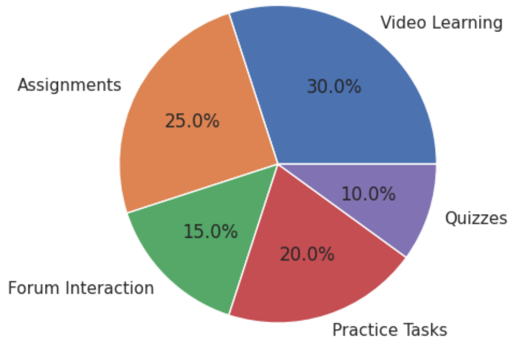

Figure 4. Distribution of Learner Engagement Across Learning Activities

The figure entails the proportional dispersion of learner engagement to the several forms of instructional activities in the digital learning environment. The pie chart depicts the way learners dedicate their time to interaction with the various aspects of learning, which are video-based learning, assignments, forum interaction, practice tasks, and quizzes. Every part of the chart indicates the proportion of contribution of a particular activity to the total level of engagement. The distribution shows that video learning takes the largest percentage of 30, assignments 25, practice tasks 20, forum interaction 15, and quizzes the lowest percentage of 10. This distribution gives clear answers to the way of interaction of learners with various learning sources in the system.

Video learning activities hold the highest percentage of engagement, and this shows that the multimedia instructional materials have a leading role in knowledge acquisition. Video-based resources can also have visual explanations, demonstrations, and guided instructional material as supplements to a more in-depth conceptual grasp. The fact that more than half of them engage with the content indicates that multimedia content is important to learners in understanding the complicated issues and reaffirming the theoretical ideas. This behavior shows the relevance of using interactive and visually rich pedagogical content in the digital education system to promote learning and long-term attention among students.

Together with assignments and practice tasks, these components account for a considerable portion of learner engagement, contributing 25 percent and 20 percent, respectively. Such activities indicate the active learning stage during which learners practice the theoretical knowledge acquired in solving practical problems. Assignments are used to make the learners analyze ideas, do some structured work, and show some comprehension by writing or acting out. Likewise, practice activities also allow learners to be reinforced and repeat, hence consolidating their knowledge of course content. The high involvement in these activities means that learners are actively involved in the processes of knowledge application as opposed to passive learning only.

Forum conversation and quizzes constitute interactive and assessment aspects of learning. The aspect of intercourse in the forum takes 15% of the participation and reflects the importance of the peer discussion and collaborative learning in the learning environment. The learners share ideas, discuss misunderstandings, and engage in knowledge-sharing activities through forums to enable a deeper thinking process. The quizzes with a contribution of 10 are formative assessment methods that enable a learner to test their comprehension of learning material. Although quizzes have a smaller percentage of engagement, quizzes play a crucial role in tracking learning progress and identifying areas that require improvement. Altogether, the engagement spread of these activities proves the balanced learning environment in which multimedia learning, practical use, collaboration, and assessment play their roles in the total learning process.

Table 2. Distribution of Learning Activity Participation

Learning Activity	Participation (%)	Learning Contribution (%)
Video Learning	30	28
Assignments	25	24
Practice Tasks	20	21
Forum Interaction	15	16
Quizzes	10	11

The table shows the proportionate learning activity of the learner participation in various instructional activities in the learning environment. Learning via videos has been recorded as the most participating tool, which implies that multimedia instructional tools are the main bases of conceptual acquisition among learners. The tasks and practice activities are also important engagement factors, which prove the relevance of task-based and experiential learning. Forum interaction is a collaborative learning in which learners share knowledge and communicate with their peers. Even though quizzes have a reduced percentage of involvement, quizzes remain necessary for assessing conceptual knowledge. All in all, the distribution shows the significance of integrating multimedia teaching, hands-on activities, group and individual discussions, and evaluation systems to reinforce holistic learner involvement.

Figure 5. Correlation Analysis of Learner Behavioral and Performance Metrics

The figure will display a heatmap of the correlation of various significant behavioral and performance measures in the learning environment. The variables used are the time spent in studying, the number of modules taken, forum activity, and quiz mark. The heatmap represents the correlation coefficient between two variables; each cell shows the value of the correlation coefficient ranging between 0.96 and 1.00. These values are really high positive correlations between the observed learning indicators. The intensity of these relationships has been visually demonstrated by the color gradient, with the least intensity having the lightest color and the highest intensity having the darkest color. These high values of correlation indicate that the academic performance indicators and the behavior of the learner engagements are interrelated in the learning system.

The correlation value between study time and forum activity is a perfect 1.00, which means that students who spend more time in the process of engaging with instructional material are also more likely to be active in the process of collaborative discussion. This trend is an indication of interdependence between individual and social learning behaviors. Students who spend more time studying want to receive more explanations or share their ideas with classmates or even engage in the discussion on the internet forums. This correlating behavior underscores the significance of learning communities to reinforce further learning and knowledge exchange among the participants.

An equally close correlation is noted between the time spent studying and quiz score, as the correlation value is equal to 0.99. This observation implies that the levels of academic performance are significantly determined by levels of engagement with learning content. Students who dedicate more time to studying learning material, reading, and interacting with materials and educational resources are likely to score better in assessment. These trends support the need to engage with learning resources over time to enhance the conceptual knowledge and academic performance of the learning platform.

The correlation between modules and quiz score is also very high, and the value is about 0.96, which means that there is a strong positive relationship between the instructional modules and the assessment performance. Students that have finished more modules will probably have a wider variety of concepts, exercises, and explanations of instructions, which makes them understand and be ready to take tests. On the whole, the high positive correlations between these behavioral indicators can be used to state that engagement, participation, and the flow of instruction have a combined positive outcome on learning outcomes and successful acquisition of knowledge in the learning environment.

Table 3. Behavioral Indicators Influencing Learning Effectiveness

Behavioral Indicator	Observed Contribution (%)	Impact on Learning Efficiency (%)
Time Spent on Learning	24	22
Video Content Interaction	21	20
Module Completion	19	18
Assignment Participation	18	17
Forum Interaction	18	15

The table shows how various behavioral indicators can be used to contribute to the overall efficiency of learning in the digital learning environment. Time spent on working with instructional materials is the contribution of the most importance to positive learning, which means that prolonged interaction means that the concepts are retained much better. Video content also plays an important role when it comes to interaction and aiding visual and conceptual understanding. Completion of modules can be considered a structured development impacting learning resources as well as a sign of systematic learning conduct. Participation in assignments and forum discussions also contributes to learning, as these activities promote the application of knowledge and its discussion. Contribution distribution reveals that the efficiency of learning depends on the interaction of behavioral factors and the role of tracking the patterns of engagement of learners in adaptive educational systems.

$$E = \frac{T + V + F}{3} \quad [1]$$

Where:
E = Learner engagement score

T = Time spent on learning activities

V = Video interaction level

F = Forum participation frequency

This formula determines the overall learner engagement by averaging three main behavioral indicators: time spent in learning activities, level of engagement in videos, and frequency of participation in forums. The engagement score is a quantitative parameter that measures the level of activity by the learners in the online learning environment and assists in determining the highly engaged learners and the less engaged learners.

$$LP = \frac{M_c}{M_t} \quad [2]$$

Where:
LP = Learning progress rate

Mc = Number of completed modules

Mt = Total available modules

The learning progress rate is a ratio of instructional modules that a learner has gone through in comparison to the number of modules offered in the learning environment. This measure is applied to assess the progress of learners via the systematic learning routes and assists in assessing the uniformity and determination in the accomplishment of learning material.

$$KPI = \frac{Q + A}{2} \quad [3]$$

Where:
KPI = Knowledge performance index

Q = Quiz score

A = Assignment score

The results of quizzes and scores on assignments are combined to determine the academic performance of learners using the knowledge performance index. This equation gives a fair evaluation of the theoretical knowledge and the practice of learning material. It assists in determining the effectiveness of learners in terms of their ability to grasp and implement instructional concepts in the process of learning.

$$AFE = \frac{P_{after} - P_{before}}{P_{before}} \quad [4]$$

Where:
AFE = Adaptive feedback efficiency

Pafter = Performance after adaptive feedback

Pbefore = Performance before adaptive feedback

This equation is an indicator of the efficiency of adaptive feedback systems applied in the learning environment. The equation will be used to assess the contribution of instructional recommendations to improvement in performance and the level of understanding of learning material by comparing the performance of learners before and after giving them personalized feedback.

$$r = \frac{\sum(E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum(E_i - \bar{E})^2 \sum(P_i - \bar{P})^2}} \quad [5]$$

Where:
Ei = Engagement value

Pi = Performance value

The correlation coefficient measures the degree of relationship between the level of learner engagement and academic performance outcomes. The presence of a strong positive correlation shows that the higher the interaction of the learners with the learning activities, the higher the performance. This formula can be applied to determine the impact of behavioral engagement on the effectiveness of learning in digital education.

$$LSE = \frac{E_g + P_g + K_r}{3} \quad [6]$$

Where:
LSE = Learning system efficiency

Eg = Engagement growth rate

Pg = Performance improvement rate

Kr = Knowledge retention rate

Learning system efficiency is a measure of the effectiveness of a learning environment based on engagement growth, improvement in performance, and knowledge retention. This equation is a total quantification of the fact that the system can assist the learner in his interaction, advancement in academic achievements, and advancement of his knowledge under long-term retention.

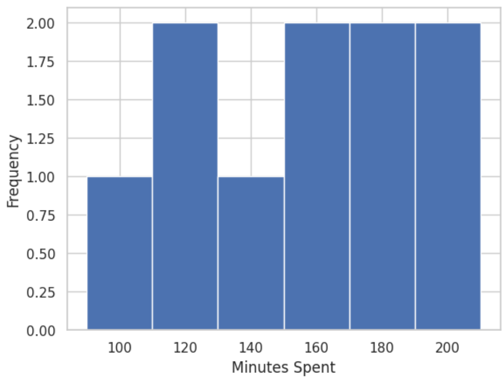

Figure 6. Distribution of Learner Study Time Across Learning Sessions

The figure shows how the learners are deployed in using instructional materials in the digital learning environment. The histogram is a way of expressing the frequency of the learners in terms of the period of the study sessions in terms of the number of minutes. The amount of time that the learners use the learning platform is recorded in the horizontal axis, whereas the frequency of the occurrences during the time periods is recorded in the vertical axis. The values depicted are in the range of about 90 minutes to 210 minutes; this indicates that there is a big difference in the time learners dedicate to the learning processes. This distribution will shed some light on the children on a case-by-case basis on their learning patterns and level of engagement during the learning sessions.

The lower limit of study time, which has values near 90-120 minutes, depicts learners with relatively low durations of interaction with learning materials. Such learners can easily browse through teaching resources or accomplish learning tasks at an accelerated rate. In other instances, the durations of engagement can be shorter because of the effective understanding of the material or the previous knowledge of the topic. But it can also mean that there is a small amount of exposure to some learning materials, which indicates that some learners can be using selective engagement strategies when working with learning materials.

There is an average extent of engagement between around 130 and 170 minutes that a larger number of learners are concentrated on. This range indicates that there is equilibrium in learning behavior, with learners taking enough time to review instructional materials, view multimedia materials, complete tasks, and engage in interactive learning processes. Students in this group are also known to be consistent in their engagement pattern, which adds to the consistency of learning. Such moderate levels of engagement are usually indicative of organized study practices and proper time management in the accomplishment of learning processes within the system.

The increased duration of time spent studying, which is around 180-210 minutes, is evidence that learners have spent considerable time studying materials. Such learners can spend more time on studying difficult material, going through the teaching materials, or doing other learning tasks to consolidate their knowledge. Longer periods of engagement indicate deep learning behavior, where students dedicate more time to understanding difficult concepts or achieving higher academic results. The availability of such a range in the distribution brings out the versatility of learner engagement patterns and underlines the significance of flexibility in instructional support to meet the different study patterns and learning demands.

Table 4. Machine Learning Model Performance Metrics

Model Component	Accuracy (%)	Precision (%)	Recall (%)	Efficiency Contribution (%)
Learner Performance Prediction	91	89	90	22
Knowledge Gap Detection	88	87	86	21
Engagement Pattern Analysis	90	88	89	20
Learning Recommendation System	89	87	88	19
Feedback Personalization	92	90	91	18

The table is a summary of the result of the performance evaluation of machine learning components applied in the adaptive learning framework. The level of accuracy in all the components is high, which means that the predictive abilities and effective analyses can be relied on. The learner performance prediction module produced high scores, and this shows its performance in predicting the performance of learners using behavioral indicators. Detection of knowledge gaps helps to identify and consolidate conceptual weaknesses among learners, enabling the provision of specific instructional support and recommendations. The analysis of engagement patterns helps to comprehend the trends in the interaction and behavior of learners. Instructional guidance is also further promoted by the recommendation system and personalized feedback modules. These findings suggest that predictive analytics and machine learning models go a long way to enhance decision-making in adaptive digital learning settings.

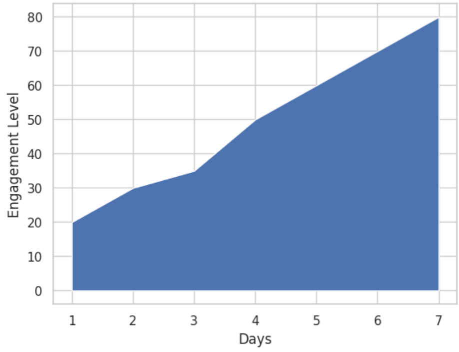

Figure 7. Progressive Growth of Learner Engagement Over Learning Days

The figure shows how the level of learner engagement can be steadily increased over a learning period of seven days in the digital learning environment. The horizontal axis is used to indicate the order of learning days, and the vertical axis is used to show the level of engagement registered among the learners during their experience with learning resources and learning activities. The colored area chart clearly indicates that there was a steady growth in the engagement levels, with the level of engagement standing at about 20 on the first day and then moving to about 80 on the seventh day. This is a trend that shows that the more the learning process goes on, the more the learners are engaged in the learning platform.

The engagement rates seem to be rather low at the beginning of the learning cycle, and the values range around 20 and rise steadily to about 35 on the third day. This phase indicates the first familiarization stage, where the learners get familiar with available learning resources and the interface and adapt to the instructional structure. At this phase, students can browse course materials, read resource introductory material, and interact with the tools. The average increase during the initial days implies that the learners are slowly getting used to the system and can start developing routine learning patterns.

It shows a significant increase in the engagement rates between the third and the fifth day, with the level of engagement increasing drastically from approximately 35 to approaching 60. Such improvement shows the higher engagement in learning activities and more active contact with learning materials. At this point, students are likely to be more involved in systematic tasks like taking up instructional units, working with multimedia resources, and trying practice tasks. The rise in activities indicates that the learners are now more engaged in the learning process and more motivated and involved in academic activities. In the last stage, which is between the fifth and the seventh day, the engagement is steadily increasing to a peak of about 80. This level is an indicator of a mature stage of interaction where the learners are always involved in the learning activities and are always active in the system. This long-term growth is a sign that learners do not only access instructional content but also have more advanced learning behaviors like revising materials and engaging in discussions as well as assessments. The fact that the trend was steadily increasing as depicted in the figure indicates the success of adaptive learning settings in promoting persistent attendance and gradually deeper involvement of learners as time goes by.

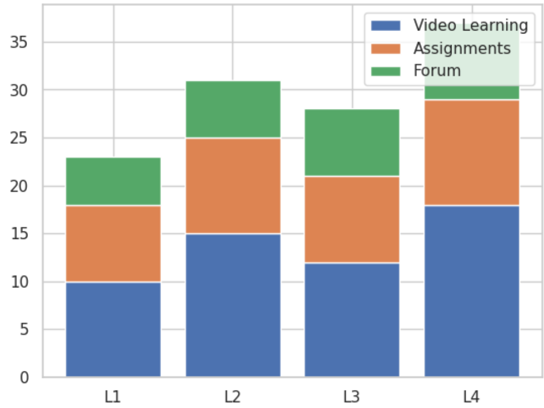

Figure 8. Comparative Participation of Learners Across Learning Activities

The figure provides a stacked bar chart that demonstrates the engagement of various learners in three key learning activities in the digital learning environment, which are video-based learning, assignment completion, and forum interaction. The bars represent a particular learner (L1-L4), and the cumulative parts are the contribution of each of the types of activities to the overall engagement of the learner. The visual representation shows how the learners allocate their efforts in the consumption of instructional content, tasks associated with assessment, and interaction among themselves. The sum of the height of all the bars depicts the overall level of engagement by the learner in all these activities.

Learner L1 exhibits an intermediate level of participation in all the activities, with video learning taking up the highest percentage and assignments and forum participation coming behind in that order. This trend demonstrates the equal balance of learning where the initial intervention is conducted with the help of multimedia resources, then learning tasks and discussion. This type of engagement indicates that students are likely to use instructional videos as the main source of conceptual knowledge and then move to assignments and social activity.

The higher level of engagement is witnessed in learner L2, with participation in all three activities being significantly bigger than in L1. Video learning constitutes the most significant part of the engagement; assignment completion and forum activity also play an important part. This trend shows a close and regular contact with the learning environment. Students who exhibit this kind of behavior tend to be more motivated and involved in the consumption of content and in practice. Their equal engagement in teaching, assessing, and cooperative activities facilitates more powerful knowledge reinforcement as well as learning progression.

There are also some interesting engagement patterns in both learners' L3 and L4, albeit with a slightly different distribution. L3 displays moderate performance in all three activities, which means that its engagement is constant, though slightly less than that of L2. L4, on the contrary, shows the most overall participation, especially in video learning and assignment completion. This implies that L4 will be exposed to instructional resources and evaluation activities, which can be part of enhanced learning. The hierarchical diagram shows that various types of engagement add towards the degree of activity during learning and the need to incorporate multimedia teaching, task evaluation, and collaboration to enhance wholesome learning experiences.

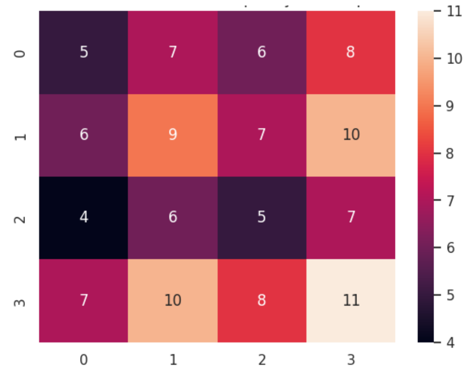

Figure 9. **Learner Interaction Intensity Heatmap Across Learning Activities**

The figure is a visual representation of a heatmap that shows the degree of interaction between the learners in various learning activities in the online learning platform. The frequency or level of interaction with a particular learner-activity combination is represented by each cell of the heatmap. The color gradient gives a visual cue of the intensity of interaction, with darker color tones depicting lower interaction values and light colors depicting higher levels of engagement. Numbers provided in the cells vary between 4 and 11, which indicates the differences in the activities involving the learners through the observed activities.

The heatmap in the first row indicates the moderate level of interaction with the range between 5 and 8. The values mean that the respective learner will be characterized by a consistent interest in the learning environment and will not show the highest levels of interaction. This kind of behavior can depict the learners that regularly access the instructional materials and get involved in the learning activities and keep a balanced learning program. The moderate levels of interaction indicate regular engagement with the system without excessive reliance on other learning materials.

The second and fourth rows have a larger interaction value, especially in the later columns, where it takes the value of 10 and 11. The increased values signify the learners who are highly engaged in the learning platform and constantly access different instructional materials and collaborative tasks. The intensity of interaction is high, which implies strong learner involvement in the learning process, including multimedia materials, assessments, and group discussions. Such behavior can be related to the further engagement of the learning environment and the increased devotion to the learning activities.

On the contrary, the third row presents relatively lower interaction values, with the lowest value of 4. This trend shows that the learner in this row is exposed to fewer learning activities than others. Reduced interaction intensity can be an indication of less interaction, less involvement in collective elements, or discriminatory use of learning materials. The recognition of such patterns of interaction is useful for studying student behavior and identifying learners who require further instruction or adaptive learning suggestions. All in all, the heatmap is an effective tool that allows us to identify differences in the intensity of interaction of learners and can give information on how various participants interact with the learning environment and how the patterns of interaction contribute to the differences in activities.

Table 5. **Improvement in Learning Outcomes After Adaptive Support**

Evaluation Metric	Before Adaptation (%)	After Adaptation (%)	Improvement (%)
Quiz Performance	78	88	+10
Assignment Completion	72	85	+13
Module Completion	75	87	+12
Learner Engagement	70	86	+16
Knowledge Retention	76	89	+13

The table shows the comparative evaluation of the learning outcomes prior to the implementation of adaptive learning support mechanisms and after. The findings indicate that there are significant positive changes in the various performance indicators when the adaptive instructional strategies are introduced. The quiz score had improved by ten percentile points, and this was a sign of a higher level of conceptual learning. There is also a significant improvement in assignment completion and progression of the module that indicates an increase in the level of learner involvement in the systematic learning processes. Learner engagement is improved the most, which is an indication of the usefulness of individualized learning journeys and dynamic feedback systems. These results show that the adaptive learning systems do play a positive role in motivating, retaining knowledge, and the general performance of the learner.

Conclusion

- The research shows that smart digital classrooms considerably improve learner interaction through the analysis of behavioral interaction patterns, including study time, the number of modules completed, and participation in group work.
- The behavioral learning analytics will be a good source of information about the progress of the learners, and it will help determine the patterns of learning, the level of engagement, and the possible gaps in knowledge within the learning environment.
- The automatic processing of machine learning methods allows predicting the effectiveness of learners and is able to automatically generate personalized instructional suggestions.
- Adaptive learning processes involve dynamically regulating the learning pathways and adaptive responses based on learner behavior and academic performance, hence enhancing learning effectiveness and knowledge acquisition.
- Their application of privacy-conserving methods means that the sensitive information about learners is not compromised and still allows conducting data-driven analysis and model development.
- The mechanisms of bias detection and fairness evaluation can assist the creation of equitable learning systems by reducing bias in algorithms and providing equal educational opportunities to different classes of learners.
- Experimental results show that the greater the learner's interaction with learning materials such as multimedia information, tasks, and discussion forums, the more academic achievement and memorization of information is provided.
- The framework proposed shows that the indicators of learner engagement and learning outcomes are associated with each other at a strong level, which suggests that it is crucial to monitor behavioral learning measures continuously.
- Combining learning analytics, artificial intelligence, and privacy-preserving measures can facilitate the creation of smart learning systems enabling customized and safe learning experiences.
- In general, the results indicate that adaptive learning systems, which are data-driven, can enhance the effectiveness of the educational process and student attitude and performance and ensure ethical and safe data handling procedures.

Data Availability Statement

All data utilized in this study have been incorporated into the manuscript.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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