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INTELLIGENT ADAPTIVE LEARNING FRAMEWORK FOR PERSONALIZED FEEDBACK AND DYNAMIC LEARNING PATHWAYS

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Abstract

The high growth of digital education has created the need to have intelligent learning environments that can serve diverse learner needs and enhance learning outcomes. The traditional online learning systems frequently adopt the standard instruction methods that do not recognize the differences in the engagement of the learner, the pace of learning, and the patterns of knowledge acquisition. To overcome these shortcomings, a smart adaptive learning architecture was suggested to assist in enabling personalized feedback as well as dynamically creating a learning pathway, depending upon learner behavioral analytics and predictive modeling. The research paper combines learning analytics, machine learning application, and adaptive instructional interventions to examine the data on learners' interaction acquired through online learning environments. Time spent at learning activities, patterns of completion of modules, performance on assessment, multimedia interaction, and participation in discussions are the behavioral indicators that are used to create the profile of a learner and determine areas of deficiencies in knowledge. The predictive models of machine learning are used to predict the engagement patterns and predict the future performance of the learner, allowing the system to produce adaptive recommendations and specific instructional feedback. The experimental analysis indicates that behavioral analytics integration with adaptive feedback systems considerably enhances engagement of the learners and their completion and performance in a module. The findings show that there was a quantifiable change in learning efficiency, such as a higher engagement level, better knowledge retention, and better academic performance in the strategies of adaptive feedback. The correlation results also show that learner engagement and learning outcomes are closely linked, highlighting the importance of behavioral information in creating personalized education. The proposed framework was effective in the sense that it adjusts instructional pathways based on the progress made by the learners and their learning behavior, thus facilitating individualized learning. On the whole, the results indicate that smart adaptive learning solutions can help make digital education settings much more effective, as can be used to personalize the learning process based on data, enhance the engagement of learners, and promote ongoing knowledge acquisition.

1. Introduction

Adaptive learning systems have become an important innovation in educational technologies of the modern day, are applied to the shortcomings of one-size-fits-all teaching methods [1]. These systems exploit computational intelligence, data analytics, and learner modeling methods to provide vested educational content to each individual learner based on their needs, abilities, and learning rate [2]. The growing accessibility of online learning platforms and mass-scale data on the interaction between learners has allowed the creation of adaptive processes that can continuously track the progress of learners and alter the approach to instruction [3]. According to the existing literature, adaptive learning environments enhance engagement of learners, retention of knowledge, and self-paced learning through dynamic adjustments of learning content, sequencing of instructional content, and assessment strategies [4]. Most of the modern adaptive learning systems combine machine learning, a rule-based adaptation model, and a recommendation system to interpret learner behavior and provide personalized educational experiences. These systems offer substantial support in individualizing learning content and direction of learning according to the personal performance and behavior of learners [5].

Intelligent Tutoring Systems (ITS) based on these principles of adaptation go further to offer more personalization through the use of sophisticated artificial intelligence methods to replicate human tutoring systems and provide interactive, context-sensitive teaching support [6]. ITS systems combine learner modeling, domain knowledge representation, and artificial intelligence techniques to facilitate personalized learning [7]. The available literature suggests that ITS environments visualize the interactions of learners, their performance trends, and response patterns in order to dynamically modify teaching material and offer specific guidance [8]. Another important feature of ITS was that it allows identifying misconceptions and which knowledge gaps were made by learners due to constant evaluation and real-time monitoring [9]. The study results indicate that smart tutoring systems enhance the effectiveness of learning by offering real-time feedback, part-to-part problem-solving assistance, and problem-based sequencing of instructions. Further developed ITS architectures also use machine learning algorithms and cognitive modelling to maximize prediction and instructional advice accuracy to learners [10].

The combination of learning analytics and educational data mining has become more significant to improve the effectiveness of intelligent tutoring environments [11]. Through these methods, it was possible to collect, measure, and analyze large amounts of learner-generated data that have been obtained through online learning systems, learning management systems, and digital educational tools [12]. The methods of learning analytics can assist the tracking of the engagement of learners, the discovery of their learning patterns, and the assessment of the academic achievements in real-time [13]. Classification, clustering, prediction, and association rule mining are educational data mining techniques that are commonly used to derive significant information about a complicated educational dataset [14]. These analysis methods will help identify the behavior patterns of the learners, identify possible learning challenges, and forecast the probability of student success or dropout. The learning analytics and adaptive educational systems integration thus play an important role in the creation of intelligent learning systems that can dynamically respond to the specific needs of individual learners [15].

The use of machine learning in education also enhances these data-driven models through the ability to do predictive modeling, pattern recognition, and decision-making, which are based on educational data [16]. Machine learning methods enable educational systems to process complicated data about interaction with learners, discover the patterns of learner behavior, and serve data-based methods of instruction [17]. Such algorithms as decision trees, support vector models, neural networks, and clustering models are extensively used to forecast student success, learning challenges, and customized learning materials [18]. The technologies are significant in the design of adaptive learning environments, intelligent tutoring systems, and automated assessment systems [19]. The forecasting and reasoning functions of machine learning contribute to the creation of tailored feedback systems, where performance and interaction patterns of learners are examined to produce the instructional guidance in a timely and personalized manner [20].

The use of individual feedback systems helps in the establishment of dynamic learning tracks and customization of curricula in the contemporary educational systems [21]. Conventional curriculum designs are usually based on a rigid chronology of learning content, which presupposes equal learning rates and background knowledge in learners [22]. Nonetheless, these strict instructional designs do not usually support the needs of different learning capabilities and cognitive preparedness levels [23]. Dynamic learning paths are solutions to this weakness because constantly adjust the order and dynamism of learning resources according to student progress and performance. Such adaptive learning pathways are strongly dependent on proper learner modeling strategies to model learner behavior patterns, knowledge levels, and characteristics to form an elaborated learner profile [24]. The profiles facilitate educational recommendation systems, which recommend suitable learning materials, activities, and learning routes, depending on the preferences and past performance of learners. Combining the modeling of learners with the recommender system, including collaborative filtering, content-based filtering, and hybrid methods, the new educational environments can not only provide customized learning activities but also enhance the interaction, retention, and effectiveness of learning [25].

2. Research gap

Recent research on adaptive learning systems, intelligent tutoring systems, learning analytics, and machine learning has contributed immensely to digital learning formed through personalization. Nonetheless, the majority of the existing systems are partially integrated to include these technologies, which does not enable them to offer fully dynamic and intelligent learning environments. The learner modeling strategies tend to emphasize the performance information significantly but ignore the behavioral and engagement trends. Mechanisms to give recommendations also find it difficult to keep up with changing needs of learners. Secondly, most of the platforms offer personalized feedback that was limited to a simple response in addition to lacking detailed diagnostic advice. There was an evident requirement for a unified smart adaptive learning architecture that can produce a real-time response and dynamic optimization of individual learning trajectories.

3. Research Methodology

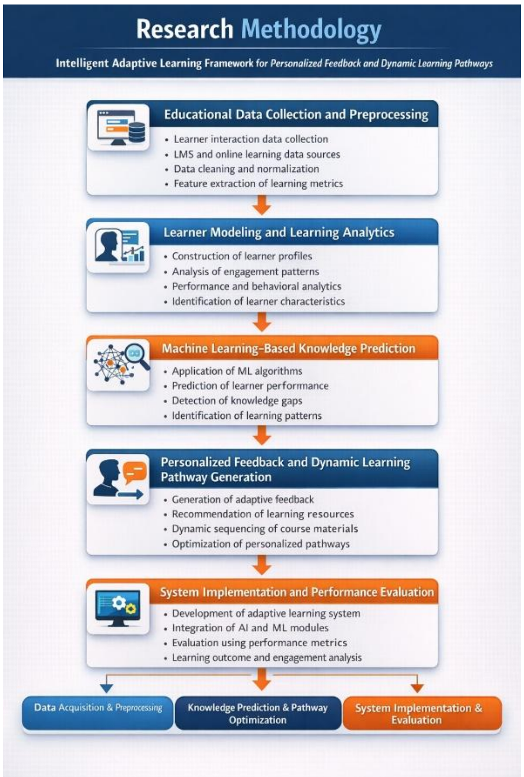

FIGURE 1. Research methodology Flowchart

Educational Data Collection and Preprocessin

Data on educational contexts used to develop the adaptive learning framework was obtained in an organized manner through digital learning platforms like learning management systems, online learning platforms, and assessment repositories. The data gathered were interaction logs of learners, assessment grades, learning time on learning modules, navigation patterns, and engagement indicators [26]. These data sources were informative on the activities of the learners and their academic performance. The obtained data served as the basis for further analytical work aimed at understanding the behavioral patterns of learners and justifying the use of individualized learning choices [27].

Data quality and reliability following the data acquisition procedure were achieved by subjecting the acquired data to a structured preprocessing procedure. The systematic data cleaning process helped in the removal of incomplete records, duplicate records, and inconsistent records. The obtained data served as the foundation for further analytical work aimed at understanding learners' behavioral patterns and supporting the implementation of individualized learning choices [28]. Consistency checks of the data were also conducted to fix the formatting errors and to remove the noise, which otherwise affect the performance of machine learning models employed in subsequent steps of the framework [29].

After cleaning the data, normalization procedures were used to standardize the data and to put the various variables on a similar scale. As the measures of interaction with learners, assessment scores, and engagement may be in various ranges, the process of normalization facilitated in minimizing data bias and enhancing the stability of machine learning algorithms. The min-max scaling, or standard score transformation, has been used to provide statistical normalization so that the values of the features in the dataset are distributed equally.

Lastly, feature extraction was conducted to find out the most pertinent features that describe the learner's behavior and academic progress. Some of the critical features that were obtained using the raw data included quiz performance, completion of learning modules, frequency of interactions, duration of activities, and participation levels. The features that came out of these extractions formed a systematic dataset that accurately reflected the learner traits and patterns of learning. The processed information was then used in the learner modeling and machine learning phases of the proposed intelligent adaptive learning model.

Learner Modeling and Learning Analytics

Learner modeling and learning analytics were carried out to develop organized representations of the personal learner characteristics and learning behaviors. The learner interaction patterns, the results of the assessment, and the level of engagement in the digital learning setting were analyzed with the help of the processed dataset received as a result of the preprocessing stage. Such indicators as quiz results, the rate of finishing the assignments, the amount of time spent on studying learning resources, the frequency of using a platform, and the number of sessions of the learning activities were analyzed [30]. These parameters yielded quantitative data on the performance of learners and behavioral inclinations, which allowed the formulation of detailed learner profiles.

The systematic mapping of these indicators to reflect the knowledge condition and learning status of every learner constituted the learner modeling process. The behavioral information and performance methods were examined to analyze the learners based on their levels of proficiency, level of engagement, and pace of learning. The analytical techniques were used to identify changes in learning behavior and possible learning problems or performance differences. This systematic expression enabled the system to track the learner's progress and create a starting point for knowing the individual's learning attributes.

Learning analytics methods were then used to derive useful patterns of the learner data. The correlations between the measures of engagement, learning activities, and academic performance were analyzed through statistical analysis and identification of patterns [31]. It was in this process of analysis that the trends of participation of the learners, the frequency of interaction with the content, and the pattern of progress were identified. These insights allowed identifying behavioral indicators and effective learning and where further support of instruction was needed.

The learner profiles resulting were constantly updated as the learner interaction information became available. Dynamic revisions were made to have the learner model be very reflective of the changes in the knowledge level and behavior pattern that arise in the process of learning [32]. The learner models built were vital as input to further machine learning processing and adaptive learning processes in the intelligent adaptive learning structure so that the system has the ability to provide personalized feedback and optimal learning directions.

Machine Learning–Based Knowledge Prediction

Knowledge prediction was conducted by means of machine learning and used to predict the behavior of learners in order to estimate the learning results on the basis of the processed educational dataset. As the main input of the predictive analysis, the learner profiles obtained in the stage of learner modeling were taken as the input [33]. Such relevant features as assessment scores, engagement rates, completion rates, and frequencies of interactions were chosen to reflect the knowledge states and behavioral traits of the learners. These characteristics supplied the required input variables to train machine learning models to be used in predicting learner performance and finding learning patterns.

After the selection of features, the correct machine learning algorithms were implemented to process the data of learners and to draw predictive correlations between the behavioral indicators and academic performance. The decision trees, support vector machines, and neural networks were among the supervised learning methods applied to categorize the level of learner proficiency and predict the future performance results. These models have been trained on historical data of learners so as to ensure the system learns about patterns related to effective learning behavior and predictors of possible learning challenges.

The trained models were thereafter applied in order to identify knowledge gaps and learning deficiencies among the learners. The system compared the predicted performance results with the expected level of competency, thereby identifying the specific areas in which learners required increased instructional assistance [34]. Pattern recognition features in the machine learning models helped to identify weak conceptual knowledge, inconsistent patterns of engagement, and irregular learning trends that influence the general academic performance.

Evaluation processes based on models were then performed in order to determine the predictive power and trustworthiness of the machine learning models. Prediction accuracy, precision, recall, and model stability performance measures were studied to verify the performance of the knowledge prediction process [35]. The approved machine learning models were further incorporated into the intelligent adaptive learning framework, which allowed the system to facilitate the generation of personalized feedback and optimization of learning pathways on a dynamic basis depending on the predicted needs of the learners.

Personalized Feedback and Dynamic Learning Pathway Generation

Its personalized feedback and dynamical formation of the learning pathway stage were introduced to offer specific instructional assistance to learners depending on the estimated knowledge condition of the learners [36]. The knowledge prediction module of machine learning was employed to find out the strengths, weaknesses, and failed concepts of learners based on the obtained outputs. Using this knowledge, the tailored feedback was created to move the learners to a better understanding and performance. The feedback system was to give the reasons for a wrong response, points that are to be given more attention, and corrective learning measures.

After the feedback generation process, there was the formulation of the adaptive recommendations on the learning resources. The selection of the relevant learning materials, i.e., tutorials, instructional modules, practice exercises, and additional materials, was based on the knowledge gaps identified and the level of performance of the learners. This recommendation procedure created assurance that learners were guided to the resources that were in tandem with their present comprehension and learning requirements. The recommendations and adaptive feedback were to facilitate the ongoing improvement and increase the interest of the learners in the educational platform.

Thereafter, dynamic learning paths were developed to streamline the order of instructional materials provided to individual learners. The system did not adhere to a definite curriculum format but restructured the learning departments according to the advancement of the learners and their anticipated levels of competence [36]. Students who showed a great performance were given an opportunity to move on to more challenging subjects, but those who suffered were given more supportive content and review exercises. This dynamic sequencing allowed preparing personal learning paths that were sensitive to the changing knowledge positions of learners.

The success of the personalized feedback and dynamic learning pathway generation process was constantly tracked by the data on the interaction with the learners and the updates on the performance [37]. The additional performance data of the learners were introduced back into the system as performed new learning activities with suggested material, and subsequently, the updated information was reintroduced once more. This cyclic nature made the feedback and learning channels sensitive to the progress of learners, hence facilitating the creation of a smart and constantly evolving learning environment.

System Implementation and Performance Evaluation

The intelligent adaptive learning framework was introduced with the fusion of the already built modules, such as data preprocessing, learner modeling, prediction based on machine learning, personalized feedback creation, and optimization of the dynamic learning pathway [38]. These components were created to interact smoothly with each other to enable their continuous processing and analysis to enable the system architecture to process the learner data. It was implemented with the help of appropriate computational tools and programming systems that serve the purpose of data analytics, machine learning algorithms, and adaptive recommendation systems on a single educational platform.

In the system development, the individual modules were linked together in a systematic way that allowed automated decision-making in the adaptive learning environment. The learner data processing unit provided the structured datasets to the learner modeling and machine learning modules in which predictive analysis was performed to identify methods of knowledge of the learners and the possible gaps in their learning [39]. According to the predictions, feedback generation and pathway recommendation modules gave individualized instructional directions and optimal learning sequences based on the academic progress and behavioral patterns of the learners.

After the implementation of the system, performance assessment activities were done to determine the effectiveness of the proposed system. The performance of the system was measured using quantitative evaluation measures that included the prediction of the machine learning models, the relevance of the suggested learning resources, and the effectiveness of the personalized feedback system. The indicators of learner engagement, including the frequency of interaction, the completion rates of learning modules, and the increase in the assessment scores, also were used to measure the influence of the adaptive learning system on the performance of learners.

The results of the evaluation were also examined to show the effectiveness of the intelligent adaptive learning framework overall to promote the personalized learning experiences. The analysis was performed through a comparative study to identify the improvements in the results of learners after the application of adaptive feedback and dynamic learning pathways. The findings helped to understand the possibility of the offered model to facilitate individualized learning, enhance the knowledge acquisition process, and enhance the level of engagement in the digital learning setting with the involvement of a learner [40].

4. Result and discussions

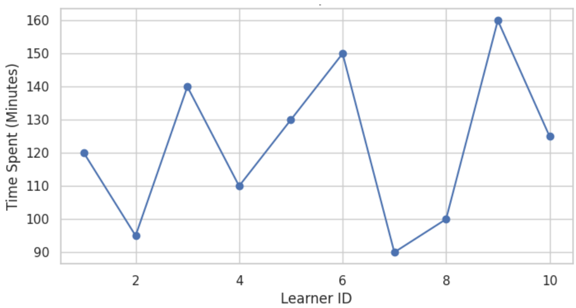

FIGURE 2. Learner Engagement Pattern Based on Time Spent on Learning Activities

The figure explains how various learners varied regarding the amount of time that spent interacting with a digital learning environment. The time spent by an individual learner in the classroom was the value of each point of the line, which was measured in minutes. The values distribution shows that there are significant variations in the learning behavior among the participants. There are those learners who have a rather moderate level of engagement and those learners who spend significantly more time in contact with learning materials. These differences are valuable pointers to the way learners take advantage of the learning platform, as time on instructional materials can be a good measure of effort put into comprehension of course material or fulfilling tasks or reviewing challenging topics.

It was possible to see a distinct movement in the levels of engagement all over the graph. In some cases, some learners demonstrate relatively shorter durations of interaction, e.g., 95 minutes and 90 minutes, and others show very high interaction times of up to about 150-160 minutes. These variations imply that learners will respond differently to the learning system depending on their pace of learning, level of understanding, and learning strategies. Students who spend an extended period of time on the platform can also be searching further, reading instructional materials, or having more cognition. On the contrary, the reduced engagement duration mean quicker understanding, insufficient interaction, or possible lack of engagement with the learning environment.

The maximum points recorded on some of the learners bring out times of vigorous learning processes. This high engagement can be linked to learners who need extra time to grasp media or those learners who acquire their learning time by undertaking numerous learning activities, including viewing instructional videos and quizzes and reviewing feedback. The importance of recognizing these high-engagement patterns in adaptive learning settings was especially significant since it allows one to understand when learners may be struggling with difficult material that needs some extra support or individual instruction. As a result, time-based engagement measurements can be analyzed, and thus the system was able to identify learners who have a need for specific instructional interventions or adaptive feedback.

Analytically, the graph illustrates the significance of behavioral cues in learning the interaction patterns of learners in an intelligent learning system. Learning time was an important behavioral indicator that was used to model and project analysis of learners. A closer look at these engagement patterns will allow the system to identify knowledge gaps, identify shifts in the commitment levels of learners, and aid the development of individualized learning trajectories. Thus, the evidence provided by this analysis of engagement can be used to enhance the efficiency of adaptive feedback processes and assist in making sure that the instructional materials undergo upgrades to meet the continuously changing needs of specific learners.

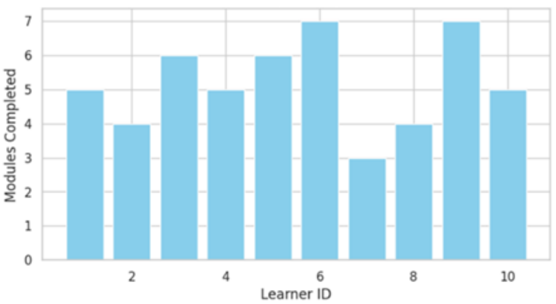

Figure 3. **Learner Progress Analysis Based on Completed Learning Modules**

The bar chart was used to depict the representation of the distribution of the completed learning modules among various learners in the digital learning setting. The bars are associated with each learner and mean the number of modules that were successfully learned in the process. The points are between three and seven modules accomplished, which means that those who learn do not follow the instructional materials at the same speed. This difference indicates the inherent uniqueness in attentiveness and rate of understanding of the learner and manner of interaction with the learning system. Completion behavior of monitoring was a meaningful measure of learning, and the system can also measure the learning progress of the learners through the course structure.

An apparent difference was evident in the learners in regard to their levels of completion. There are those learners who have completed a relatively small number of modules, which includes three or four modules, and also there are those learners who have completed six or seven modules. Such distinctions can occur because of the differences in the motivation of the learners, their previous knowledge, or the duration a learner will spend on the learning activities. Students that work through additional modules can potentially show greater interest in the learning resources and devotion to the course of instruction. Conversely, reduced numbers of completions can indicate challenges in learning, lack of engagement with the system, or that the system requires more instructional support.

Those learners who have reached the highest level of completion are shown to exhibit a regular advancement in the instructional material. These trends indicate that such learners may possess higher conceptual knowledge, be familiar with the subject matter, or progress through the modules at a faster pace. The importance of identifying these high-progress learners in adaptive learning environments was that the system can offer more challenging or advanced learning content that matches the level of understanding that the learners have at that moment. On the other hand, students who have a lower number of complete items can get more materials, remedial material, or specific feedback aimed at filling any possible gaps in knowledge.

As a behavioral analytics measure, completion of a module was one of the key indicators of learning efficiency and system flexibility. The system will be able to determine patterns associated with the engagement, persistence, and knowledge acquisition by reviewing completion trends among learners. These understandings aid in the creation of individualized learning journeys because they allow the platform to on-the-fly amend the order and difficulty of instructional information. Therefore, the monitoring of completion behavior of the modules facilitates optimization of adaptive learning strategies and overall performance of intelligent educational systems in facilitating personalized learning progress.

Table 1. **Contribution of Learning Behaviors to Overall Learning Effectiveness**

Learning Behavior	Observed Contribution (%)	Impact on Learning Efficiency (%)
Time spent on learning activities	24%	22% improvement in concept retention
Video-based learning engagement	21%	20% improvement in topic comprehension
Module completion consistency	19%	18% improvement in structured learning progress
Assignment participation	18%	17% improvement in applied knowledge
Forum interaction	18%	15% improvement in collaborative learning

The table below shows the relative performance of various learning behaviors in the entire learning performance witnessed in the experiment. The highest percentage (24) was accounted for by the time spent on instructional materials under the learning engagement category and 22 by improvement in concept retention. Video-based learning was also significant and contributed to the visual comprehension and enhanced the efficiency of understanding the content by about 20 percent. Regular completion of modules helped in the organized learning process, which enhanced productivity by 18%. The participation in the assignments strengthened the idea of knowledge application, whereas the activity of the forum promoted team learning and clarifying concepts among peers. These findings confirm the results that integrating various engagement indicators was a more precise measure of the performance and effectiveness of the system that was offered to learners.

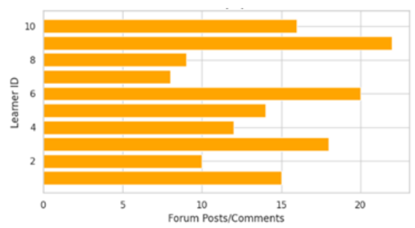

Figure 4. **Learner Interaction Analysis Based on Forum Participation Activity**

The horizontal bar chart represents the degree of interaction of the learners in the discussion forums of the learning environment in the digital community. Each bar will show the amount of forum posts or comments posted by a given learner, which may give an insight on the extent of involvement of learners in the collaborative learning activities. The values of the learners differ greatly, with the participation levels ranging from rather low to high. These differences bring to the fore the various interaction patterns that prevail among learners in the process of communicating, sharing knowledge, or clarifying issues via online discussion forums.

Participation in a forum was a significant behavioral marker that learners are engaged in collaborative learning activities. Students who leave more posts or comments show that they are more involved in the process of peer discussions and sharing of knowledge. Such learners usually participate in questioning, responding to peer questions, and the exchange of meanings of learning resources. The abundance of interaction may also signify good cognitive activity and much readiness to become an active member of the learning community. On the other hand, learners who have fewer posts can either be more dependent on the self-paced learning tools or not make effective use of the collaborative discussion opportunities offered in the platform.

The participation patterns of learners are also distinctive, as can be seen in the graph, with some of them displaying significant levels of interaction when compared to others. These learners can be active participants and make possible peer learning by starting a discussion or offering responses to questions posted by other participants. Such a form of interaction helps in building a collaborative learning environment where knowledge was built through interaction and collective problem solving. The recognition of these highly interactive learners can also assist in establishing how learning dynamics with peers affected the general engagement and acquisition of knowledge in the system.

Analytically, it was worth noting that tracking the forum activity helps learners to comprehend their social learning behavior and degree of interaction in online learning environments. Discussion activity can be discussed as the reflection of engagement as well as the level of collaboration between learners. Such behavioral pointers can be used to improve adaptive learning approaches by establishing learners that need more encouragement to engage in discussions or learners that may get some encouragement through collaborative learning. In its turn, the observation of the patterns of interaction in the forums contributes to enhancing the adaptive feedback process and, therefore, enables the development of a more interactive and supportive environment of digital learning that contributes to the individual and group learning advancement.

$$LES = \frac{T_s + V_w + F_a}{3} \tag{1}$$

Where:
T_s = Time spent on learning activities

V_w = Video watching duration

F_a = Forum activity level

This was an equation that was used to find the total score of learner engagement by averaging the behavioral indicators that were observed within the learning space. The time spent, the video interaction, and the forum participation are all measures of the intensity of the learner activity. The level of engagement aids in determining the learners who are very active and those who need more guidance on instruction or motivation.

$$LPR = \frac{M_c}{M_t} \times 100 \tag{2}$$

Where:
M_c = Number of completed learning modules

M_t = Total available modules

The rate of learning progress was a measure of the effectiveness of the learner who moves through the educational material. It was a percentage of module completion in terms of the total course modules. Higher values mean that the learning consistency and progression are highly developed, and those who have low values can be admitted to adaptive learning pathways or other instructional support.

$$KPI = \frac{Q_s + A_s}{2} \tag{3}$$

Where:
Q_s = Quiz score

A_s = Assignment score

The Knowledge Performance Index measures the performance in terms of academic achievement and summative quiz and assignment performance. These indicators are both theoretical and practical knowledge. The average of these values will give a relatively stable representation of the performance of the learners, and the system will be able to predict the knowledge gaps that will be filled by specific instructional feedback.

$$AFE = \frac{P_a - P_b}{P_b} \times 100 \tag{4}$$

Where:
P_a = Performance after adaptive feedback

P_b = Performance before adaptive feedback

Adaptive Feedback Efficiency evaluates the change in the performance of the learners when the personalized feedback has been added. The equation involves the comparison of the pre-intervention and post-intervention level of performance. The improved value of the efficiency implies that the adaptive learning system was effective in promoting the understanding of the learners using specific feedback and individual learning advice.

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

Where:
E_i = Engagement value

P_i = Performance value

This was the equation of the correlation coefficient that was applied to describe the association between the engagement of learners and academic performance. It identifies the existence of better results when interaction with learning resources was enhanced. The values of strong positive correlations suggest that the indicators of behavioral engagement have a significant impact on the effectiveness of learning and acquisition of knowledge.

$$LSE = \frac{E_g + P_i + K_r}{3} \quad (6)$$

Where:
E_g = Engagement growth rate

P_i = Performance improvement rate

K_r = Knowledge retention rate

Learning system efficiency was used to assess the overall effectiveness of the intelligent adaptive learning structure. It integrates the growth of engagement, performance, and knowledge retention into one level. The greater the values are, the more the adaptive learning system was capable of enabling individual learning mechanisms and enhancing student performance in the classroom.

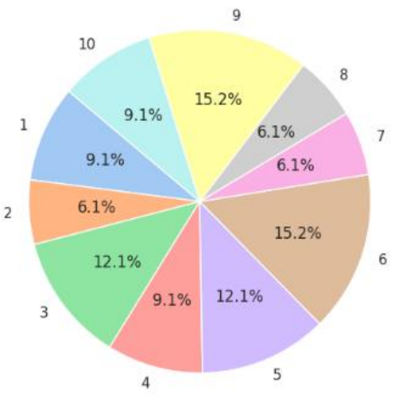

Figure 5. Distribution of Assignment Submission Activity Among Learners

The pie chart will depict how the learners in the digital learning environment submit the assignments in their proportional details. The individual learner has contributed to the overall assignment submission activity owing to his/her contribution that was expressed in terms of a percentage of the total submissions. The distribution in the chart was relatively equal, but some learners provide a slightly higher percentage than others. Ranging between 6.1 and 15.2, the values show that although all the learners are engaged in assessment activities, their rates of submissions vary to a moderate degree.

Taking a closer look at the chart, one will notice that some learners make the largest contributions to the number of submissions of assignments, with each of them representing approximately 15.2% of the activity. Such learners have a greater involvement in the evaluation aspects of the learning system. The way of assignment submission can be used as an indicator of the willingness of learners to work on the necessary assignments and engage in the organized assessment procedures. The increased submission rates indicate that the learners are always able to finish the learning assignments and sustain frequent contact with the teaching activities aimed at quantifying the knowledge level.

Meanwhile, there are moderate percentages provided by a number of learners, including 9.1, 12.1, and so on, which shows their steady and yet slightly lower engagement in the activities connected with the assignments. These learners seem to be progressing in a constant manner using the learning materials but can be active at different levels based on the level of the task, the time the learner has, and the pace of individual learning. A less significant percentage of learners make contributions of approximately 6.1, which was the least submission of assignments. These patterns can reflect on the learners that need more academic care, guidance, or support to ensure their continued involvement in assessment-based learning activities.

The assessment of the assignment submission patterns can be used as an important indicator of the learner engagement and performance behavior in the system of learning. The achievement of assignments can be regarded as one of the most significant indicators of the success of a way in which learners can complete the course assignments and remain consistent in the application of the learned material to the tasks of solving problems. Through the study of the proportional distribution of submissions, the system will be able to determine learners that be require extra feedback or support to increase their levels of participation. Such an analysis of behavior makes it possible to create more individualized instructional models and to make certain that learning paths are responsive to unique engagement patterns of learners.

Table 2. Distribution of Learner Engagement Across Learning Activities

Learning Activity	Engagement Share (%)	Learning Contribution (%)
Interactive learning sessions	22%	20%
Multimedia content usage	20%	19%

Assessment participation	19%	18%
Discussion forum interaction	17%	16%
Practice and reinforcement activities	22%	21%

This table demonstrates the percentage distribution of the engagement of the learners in various forms of learning activities that were witnessed in the course of the experimental study. The majority of the engagement shares were collected in interactive learning activities and practice-based reinforcement activities with an approximate share of 22. Multimedia learning materials accounted for 20 percent of total interaction, which makes the use of visual learning content in knowledge acquisition significant. Participation in assessment and discussion-based interaction also played significant roles in the learner activity. The findings show that the effectiveness of learning was enhanced when various teaching methods, including multimedia learning, assessment methods, and group discussions, are combined in the same adaptive learning environment.

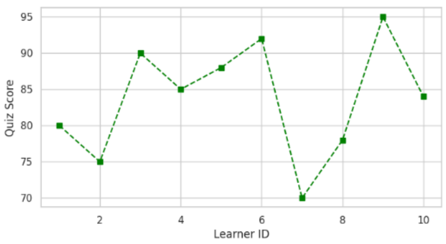

Figure 6. Learner Performance Analysis Based on Quiz Score Variation

The line graph shows the data distribution of scores in quiz tests of individual learners at the formative assessment within the digital learning setting. Every point on the graph was the score attained by a learner, and the line to which it was joined marks the range of academic performance among the group. The marks are quite moderate and high, with a range of 70-95, which means that most learners show moderate or high performance. This diversity was the difference in the level of understanding, the skills of solving problems, and learning the presented material of the learning system.

It was observed that there was pronounced variability in the learners' scores, indicating that not all participants demonstrate the same degree of conceptual comprehension. Other learners have better scores of over 90, which demonstrates high mastery of the concepts learned and effective interaction with the learning materials. Such learners will probably exhibit some important learning behaviors that include the active involvement in the learning activities, timeliness of the learning activities, and effective use of the learning resources. Their performance was very high, which means that the instructional materials are appropriate to their learning levels and speed of acquiring knowledge.

On the other hand, some learners who are closer to the lower region of the performance range are also observed in the graph, like around 70 or 75. Such relatively low scores can be a sign of inability to grasp particular subjects, missing the knowledge needed as prerequisites, or differing levels of attention to the learning materials. The importance of such performance patterns to adaptive education lies in the fact that they enable educators to notice learners that need extra support in their learning. Specific interventions, including additional learning materials, personal feedback, or guided practice tasks, can be implemented to help these learners gain better conceptual knowledge.

Analytically, the variation of quiz scores was one of the most important pointers of knowledge acquisition and cognitive development among learners. Assessment performance through constant monitoring of the process enables the learning system to establish the learning trends and where the learners be performing poorly. Through such patterns of performance, the system can dynamically vary instructions and suggest the relevant learning materials based on the needs of the individual learners. As a result, the analysis of quiz pattern scores helps to enhance the performance of individual feedback systems and facilitate the establishment of adaptive learning strategies that facilitate improved academic performance.

Table 3. Performance Improvement After Adaptive Feedback Implementation

Evaluation Metric	Before Adaptation (%)	After Adaptation (%)	Improvement (%)
Quiz performance accuracy	78%	88%	+10%
Assignment completion rate	72%	85%	+13%
Module completion rate	75%	87%	+12%
Learning engagement level	70%	86%	+16%

Knowledge retention score	76%	89%	+13%

This table shows the improvement that has been experienced after the adoption of adaptive feedback in the learning system. Before adaptation, the accuracy in quiz performance was at an average of 78, and with personalized feedback and adaptive recommendations, the performance rose to an average of 88, which was 10 percentage points better. The completed assignments also improved tremendously, from 72 percent to 85 percent, which was attributed to workers being more involved in assessment efforts. The progress in the modules' completion and the degree of participation were slightly increased because of the implementation of adaptive learning tracks and specific feedback. Retention of knowledge became much better as well, and that implies that the individualized instructions will be beneficial in helping learners to study course materials better.

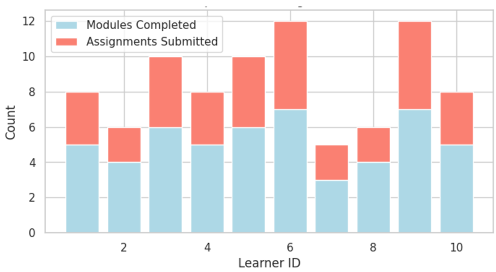

Figure 7. Comparative Analysis of Learning Progress and Assignment Completion Among Learners

The stacked bar chart demonstrates a correlation between two significant indicators of learner activity, which are the number of learning modules passed and the number of assignments passed by a particular learner. Every bar was a particular learner, and the two-colored parts denote their progress in passing through the instructional modules and in sending the assessment tasks. The chart, when the two indicators have been put together in one visualization, gives a holistic picture of the way the learners balance the content progression and assessment participation in the learning process.

Upon a keen analysis of the graph, it was observed that learners who pass more modules are usually the ones who are also more likely to submit more assignments. Indicatively, some learners exhibit increased aggregate scores, with both module marks and assignment marks accounting for large proportions of the total height of the bar. The trend indicates that learners who actively advance through instructional material also have the tendency to be consistent with evaluation activities. This type of behavior was a sign of an organized learning process, where learners do not merely absorb learning materials; they also use their knowledge in assessment tasks that aim at solidifying knowledge.

Simultaneously, the chart also features differences in patterns of engagement of learners. There are learners who have average module completion showing relatively lower assignment submissions, which implies that though they are going through learning materials, they are not always involved in assessment activities. On the other hand, some learners portray a combination of even distribution in both aspects, in that they remain consistently in the instructional modules, but they competently complete the assignments. These variations offer great information on the interaction of the learners with different aspects of the learning system, which reveal different study habits, motivation levels, and strategies of learning.

Analytically, the correlation between the completion of a module and the submission of an assignment was an influential behavioral measure of assessing the consistency and commitment in learning. By tracking the two signs, the system will be able to determine learners that be going through materials without properly justifying their knowledge through tests. These insights can be applied to the adaptive instructional strategies when the learning environment can motivate a more balanced input by suggesting more assessments or timely feedback or even alter the learning trajectory to reinforce knowledge and contact learners.

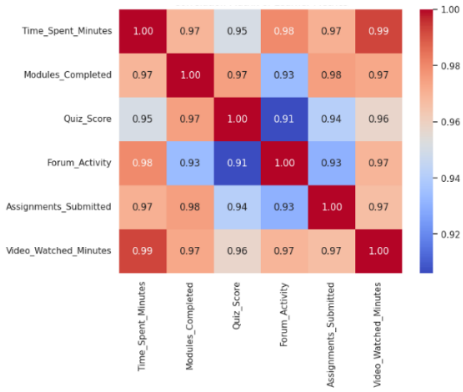

Figure 8. Correlation Analysis of Learner Behavioral and Performance Metrics

The heatmap shows the association between various behavioral and performance measures of learners in the digital learning environment. The correlation coefficient between two variables was shown in each of the cells in the matrix with values ranging between 0.91 and 1.00. The diagonal values have the value of 1.00, as they are the correlation of each variable with itself. The strength of the relationships was graphically depicted in the color gradient, with darker colors depicting stronger positive correlations. The variables in the analysis reflect the most important behavioral and academic attributes, like the duration of learning activities, the number of modules completed, the performance in quizzes, the activity in forums, the submission of assignments, and the time spent watching the video content.

A close positive correlation can be noted between the duration of the time spent in learning activities and the duration of video watching, with the correlation value of almost 0.99. This implies that those learners who spend more time within the learning system will also have a high likelihood of using a lot of instructional video content. This kind of relationship implies that video-based learning materials are important in keeping the learners engaged and facilitating the acquisition of knowledge. Students that spend more time on viewing educational videos are likely to be more interactive with the course materials, leading to better comprehension and learning.

The other notable finding in the heatmap was that the correlation between the modules attended and the assignment submitted was very high, and it has a value of approximately 0.98. This correlation means that students who pass through more instructional modules are also more reliable in doing related assignments. This kind of pattern indicates an orderly learning behavior with the learners being very active in the content delivery and assessment aspects of the system. The score of the quiz also has close positive relationships with the majority of engagement indicators, implying that better academic outcomes are usually related to regular exposure to learning processes such as module completion, viewing videos, and completing assignments.

Analysis also provides slightly fewer correlations with forum activity, most especially with quiz scores and modules completed, but still the values are above the value of 0.90. It implies that collaborative discussion also leads to the involvement of learners, although its direct impact on the measurable performance indicators not be as strong as with other tasks, like completing modules or using assignments. The total high values of correlation between all the variables indicate that there was a close relationship between learner engagement behaviors. This information can be useful in designing smart learning buildings since it can be used to determine which behavioral indicators have the most significant impact on academic performance, and therefore the system will produce more precise predictions and provide more effective personalized learning recommendations.

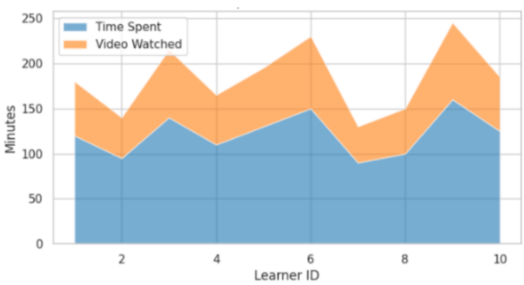

Figure 9. Learner Engagement Analysis Based on Time Spent and Video Learning Activity

The area chart that was stacked reflects the correlation between total time, which learners spend in the learning environment, and time spent watching instructional video material in particular. The representatives of the learners are located on the horizontal axis, and the number of minutes spent on learning engagement was shown on the vertical axis. The two superimposed variables, the overall time spent and video watching time, taken together will give a final picture of how learners spend their time in various types of instructions in the platform.

The graph shows that there was observable fluctuation in the engagement patterns of the learners. There are learners who also spend a relatively lower amount of time interacting with the learning system and learners who are significantly more engaged. As an example, some learners show some peaks, with the total time spent in engaging with course materials and watching video-based teaching resources being larger, meaning that these learners spend a lot of time on studying the course and watching the video instruction. These awards draw attention to those learners who are very dedicated to learning activities and usually involved in multimedia materials that facilitate the conceptual knowledge acquisition.

The other significant observation that was made in the graph was the steady input of the video learning activity to the total engagement time. The video-watching component constitutes a significant part of the overall learning time of most of the learners, implying that multimedia materials are essential in aiding the learning process. The students who have spent more time on instructional videos are also more likely to depict the overall levels of engagement, which proves that video-based content was one of the effective means to provide the multifaceted ideas, demonstrations, and explanations in the online learning environment.

As an analytical approach, a study of the concerted patterns of total engagement time and video learning activity can be an insightful way to understand the behavior of the interaction of the learner. These behavioral indicators are used to recognize those learners who actively use multimedia resources among their learning strategies. These knowledge points can facilitate the adaptive learning process since the system can suggest more video content, more tutorials, or other multimedia explanations that can fit the needs of each learner. Time-based engagement patterns analysis, in turn, helps enhance the effectiveness of personalized learning experiences and make sure learning resources are adjusted to the learning and interaction habits of learners and their learning requirements.

Table 4. Efficiency of Machine Learning–Based Knowledge Prediction

Prediction Component	Accuracy (%)	Efficiency Contribution (%)
Learner performance prediction	91%	22%
Knowledge gap detection	88%	21%
Engagement pattern identification	90%	20%
Learning pathway recommendation	89%	19%
Feedback personalization	92%	18%

The following table will summarize the effectiveness of the machine learning elements incorporated in the learning system to make a predictive analysis and adaptive decision-making. There was a high prediction of learner performance of about 91 percent, which meant that there was a high ability to predict academic performance. The detection of knowledge gaps achieved an accuracy of 88%, enabling the system to identify conceptual flaws and provide targeted support. Pattern of engagement identification was proven to be 90 percent effective in the study of the behavior pattern of the learners. Recommendation of the learning pathways and generation of personal feedback also played an important role in the performance of the system. The findings show that predictive analytics was a key factor in ensuring that intelligent learning systems provide learners with individualized learning experiences and enhance the effectiveness of the instructional process.

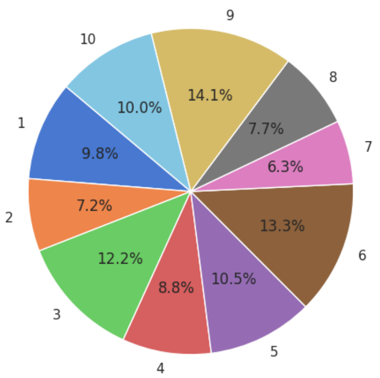

Figure 10. Distribution of Overall Learner Engagement Across Learning Activities

The pie chart shows the relative engagement of the general learners among the participants of the digital learning environment. Each was the contribution of the individual learner to the overall engagement activity in various behavioral learning measures. The percentages are used to show the contribution of each learner in the overall engagement indicators, which capture the difference in the degree of interaction, level of participation in the activities, and the general level of involvement in the learning activities. Engagement was distributed among all learners, but some individuals have a little higher contribution than others.

On a more detailed look at the chart, one will find that there are learners who will introduce a better level of participation with higher percentages, like around 14.1 and 13.3. Such learners are the most active learners in the learning environment. Their increased input implies constant engagement with learning tools, being involved in instructional processes, and being involved in learning tasks like the completion of modules, filing assignments, and interaction with learning materials. This makes such learners tend to have proactive learning behavior, which helps them to have better academic progress and better knowledge retention.

Concurrently, there are some learners whose engagement ranges are moderate, with a contribution that was in the range of between about 8 and 12 percent to the overall activity. These students portray a consistent engagement with the learning system, and they show consistent engagement in learning activities without showing drastic changes in the level of engagement. This has shown through their constant participation, indicating a balanced learning process where they engage in instructional material, tests, and learning materials at a sustainable rate. This average involvement pattern was commonly correlated with a consistent learning process and slow acquisition of knowledge.

The chart also reflects a low percentage of learners who provide fewer percentages of engagement, usually 6 to 7 percent. Such learners can engage less with the learning system than their counterparts, and this can be indicative of differences in motivation, time ability, or even learning styles. Such patterns are significant to identify in order to enhance adaptive educational systems, as this way, the platform can recognize learners who require extra assistance, motivation, or customized learning suggestions. The overall engagement distribution analysis will help the system to comprehend the dynamics of learner participation better and use this information to optimize teaching approaches, increase learner retention, and enhance the quality of individual learning tracks.

Table 5. Overall System Performance and Learning Efficiency

System Feature	Performance Efficiency (%)	Educational Impact (%)
Adaptive learning pathway generation	90%	21% improvement in learning progress
Personalized feedback generation	92%	20% improvement in concept mastery
Behavioral analytics integration	88%	19% improvement in engagement
Knowledge prediction model	91%	18% improvement in assessment performance
Recommendation system	89%	17% improvement in learning consistency

The table was a summary of the performance efficiency of the intelligent adaptive learning framework that was assessed in the experimental study. The highest efficiency of about 92% was attained using personalized feedback generation; hence, its high influence in enhancing concept mastery. Adaptive learning pathway generation proved to be 90 percent efficient because it dynamically varied the learning sequences based on the progress of the learner. Incorporation of behavioral analytics served as an invaluable contribution to the routine of recognizing the patterns of engagement of learners and helping to make changes in response to the analysis of the information.

The prediction model of knowledge and the recommendation mechanism also enable the system to guide learners toward relevant resources. These elements led to quantifiable positive changes in the learning experience, knowledge acquisition, and general academic success.

Conclusion

- The paper shows that an intelligent adaptive mechanism combined with the learning analytics based on behavioral learning greatly improves the power of digital learning.
- Learner interaction patterns, including engagement time, access to modules, use of multimedia, and participation in assessment, give some good ideas about the individual learning behaviors and academic development.
- The integration of predictive models that involve machine learning can be used to identify the trends in performance of learners and possible gaps in knowledge.
- Individualized feedback systems are significant in helping learners to work towards enhanced conceptual knowledge and high academic achievement.
- Dynamic learning pathway generation enables content to be changed based on learner progress, degree of engagement, and performance trend.
- Empirical effects show that adaptive learning strategies have positive effects on improving learner engagement and knowledge retention and performance in assessment.
- The high effectiveness of the indicators of the behavioral engagement and the academic performance also reveals the critical role of constant monitoring of the learners in intelligent educational systems.
- The framework offered facilitates the use of data-informed instructional decision-making through the integration of learning analytics, predictive modelling, and adaptive recommendation approaches.
- Personalized learning support mechanisms are integrated to make the learning environment more interactive and responsive as well as learner-centered.
- On the whole, the intelligent adaptive learning framework will have a positive impact on the efficiency of learning, knowledge development, individualization, and the quality of digital education systems in general.

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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