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AI-Powered Personalized Learning Path Generator

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ABSTRACT: - Conventional e-gaining knowledge of systems regularly provide identical content to all users, failing to house the diverse wishes of beginners. Despite the truth that every pupil has special abilties, objectives, and getting to know preferences, maximum structures provide the same content material, which lowers engagement and produces subpar effects. This looks at introduces an AI-Powered Personalized Learning Path Generator, a smart gadget that generates customized learning reports by using utilizing actual-time information and artificial intelligence. To check user profiles, overall performance trends, and getting to know behaviors, the system makes use of a advice engine based on system studying alongside generative artificial intelligence. It reorders subjects, shows applicable substances, and modifies issue stages based at the learner's development. To assure scalability, responsiveness, and steady records management, the framework uses a MySQL database, FastAPI backend, and React.Js frontend. Comparing the advised system to standard e-getting to know fashions, experimental tests exhibit a sizable development in getting to know performance, engagement, and knowledge retention. When given adaptive studying paths, college students carried out better and were greater influenced. This have a look at highlights how synthetic intelligence has the capacity to transform traditional education into a more scholar-concentrated, information-pushed, and personalized revel in that constantly adjusts to each pupil's particular instructional requirements.

INDEX TERMS:- Education generation, smart tutoring structures, generative AI, learning analytics, advice systems, data-driven education, personalized gaining knowledge of, machine getting to know, adaptive learning systems, gaining knowledge of path creation, and synthetic intelligence (AI)

(i) INTRODUCTION

Due to its affordability, flexibility, and accessibility, e-studying has emerged as one of the maximum a hit strategies of handing over education. Thanks to online systems, students anywhere can now get right of entry to pinnacle-notch academic substances whenever they need. The majority of conventional e-studying platforms, but, hold to perform on a one-size-suits-all foundation, giving all college students the equal commands no matter their pastimes, pace, or history. Poor gaining knowledge of results and decreased engagement are regularly the outcomes of this lack of personalization.

This revel in might be revolutionized with the resource of artificial intelligence (AI), that could make mastering greater individualized and adaptive. AI can monitor a

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learner's take a look at conduct, investigate their common overall performance, and recommend content that is appropriate for their interests and potential degree via the usage of smart facts evaluation.
AI-driven structures can provide customized mastering pathways in location of static substances, with the kind, order, and trouble of the content fabric converting dynamically steady with the learner's improvement.AI-pushed systems can offer personalized mastering pathways in location of static substances, with the sort, order, and trouble of the content material material changing dynamically according to the learner's improvement.

to greater complicated fabric, making sure regular development without boredom or frustration.
The proposed have a look at introduces an AI-Powered Personalized Learning Path Generator, designed to provide a whole adaptive gaining knowledge of experience. It combines 3 key components:
1. Knowledge Tracing: which tracks how nicely a learner understands special topics.
2. Learning Mode Adaptation: which identifies the handiest way to supply content material.
Recommendation Engine, which suggests suitable materials and updates the learning direction the use of real-time comments.

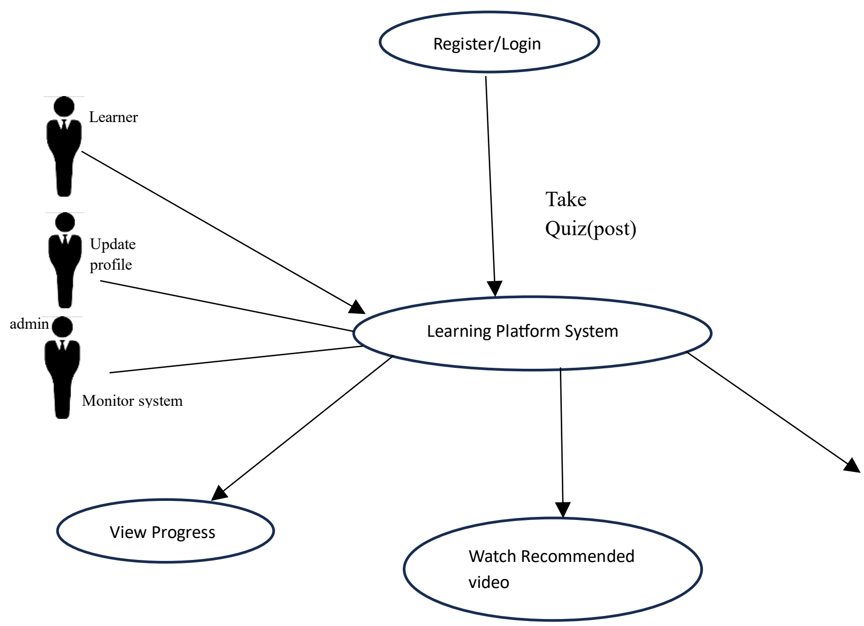
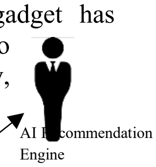
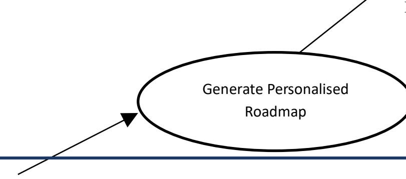


Fig 1: AI-Powered Personalised learning path generator

An AI-based definitely adaptive gaining knowledge of system, in assessment to conventional structures, designs a unique studying course for each customer. Using ordinary overall performance metrics like quiz beffects, topic time, and interplay frequency, it assesses their comprehension. The gadget can then adapt the way instructions are brought to the learner's desired fashion, whether or not that be via interactive sporting sports, text, or snap shots. For instance, the machine also can endorse quizzes or video tutorials to college college students who're having problem knowledge a specific assignment. Should the scholar excels, it advances them

This type of personalisation is specifically treasured in nowadays's hybrid and far-off learning environments, wherein rookies need non-stop assistance both inside and outside the classroom. AI structures can enhance conventional teaching by means of presenting adaptive digital content that meets each learner's wishes even as retaining affordability and scalability.
Despite its benefits, creating such a gadget has drawbacks, which include the want to address sparse information, keep privacy, make certain





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transparency in AI choices, allow actual-time scalability, and appropriately profile novices. A successful framework need to use machine learning and deep studying strategies to enhance its hints, update learner profiles, and constantly study from user interactions.

The objective of this work is to create a beneficial and efficient AI-driven framework that mixes generative AI, adaptive algorithms, and sensible advice structures to provide individualised studying reports. This have a look at also examines current tactics, identifies problems, and indicates a cohesive approach for developing adaptive gaining knowledge of paths in real-time.

(ii)METHGODOLOGY

The procedure used to create the AI-Powered Personalised Learning Path Generator is described in this segment. Starting with a review of previous research, the whole research process turned into planned to be methodical. It continued with the layout, improvement, and evaluation of the counselled device.

A vast overview of the literature on AI-based instructional systems and personalised getting to know became the first step in the process. The selection of studies papers was based on their attention on adaptive or clever mastering technology, book best, and relevance. The obstacles of present-day systems, studies gaps, and current challenges were all recognized with the aid of this overview.

A mixed-approach method was used, integrating quantitative validation through prototype implementation with qualitative analysis from the literature. In order to ensure powerful information dealing with, scalability, and responsive overall performance, the gadget became constructed with React.Js for the frontend, FastAPI for the backend, and MySQL for database management.

Throughout machine development, learner interactions and simulated inputs had been analysed as part of an ongoing evaluation technique. Analytical graphs and dashboards had been used to visualize the results as a way to determine gaining knowledge of efficiency, accuracy, and engagement.

All things considered, this methodology ensures each practical relevance and technical robustness. It establishes a robust foundation for growing wise and bendy customised e-getting to know environments via fusing theoretical understandings from earlier studies with sensible software.

(iii) Needs and Difficulties

Several prerequisites should be met in an effort to increase an AI-powered customized studying system that ensures flexibility and successful personalisation. The goal is to increase a machine that recognises the abilities and choices of each learner and then modifies the content in actual time to sell stepped forward mastering outcomes.

1. Adaptivity: Depending on every learner's overall performance, the system ought if you want to adjust the content material's kind and degree of trouble. While more skilled college students can development to more difficult subjects, individuals who are having trouble know-how a idea have to accept clearer causes or more practice.

2. Adaptability: The gadget should offer content in a variety of codecs, along with interactive sporting activities, movies, quizzes, and text notes, because every learner has a desired approach of getting to know. This guarantees that students interact with the content material but satisfactory suits them.

3.Three Continuous Assessment: Monitoring scholar progress and pinpointing areas for improvement require ongoing tests. Frequent remarks allows the device to appropriately personalise learning paths and replace them dynamically.

4. Four Data Collection and Analytics: To examine behaviour and enhance the precision of tips, the gadget desires to collect complete learner facts, together with quiz outcomes, time spent, and engagement stages. Effective actual-time personalisation is ensured with the aid of dependable facts management.

5. AI-Driven Recommendation Engine: To endorse appropriate subjects and sources, an intelligent advice engine should make use of learner records and behavioural patterns. As the learner advances, these guidelines have to trade to ensure ongoing version.

6. Knowledge Tracing: This characteristic aids the system.

B. Challenges

A number of technical and realistic troubles must be resolved while developing an AI-powered customized studying system in an effort to assure accuracy and green operation.

1. Feature Identification: It's crucial to select the ideal learner characteristics, which include ability level, engagement length, and favoured subjects. Features which might be misguided or lacking could make suggestions less effective.

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2. Content Generation: It takes time and consistency to create bendy content in a whole lot of codecs, together with textual content, videos, and interactive sporting events. The gaining knowledge of objectives and excellent have to be constant throughout all formats.

3. Three Knowledge tracking: It's hard to maintain song of the way well a pupil comprehends each subject. Numerous flaws can lead to a unmarried incorrect response, making it challenging to pinpoint the ideal concept that calls for reinforcement.

4. Four Continuous Assessment: Over time, novices' performance and behaviour evolve. To save you making unnecessary or out-of-date changes, the system ought to determine how regularly to analyse development and update pointers.

5. Learner Preference Detection: It can be hard to determine every learner's preferred technique of mastering. Combining each techniques guarantees extra personalisation, even though surveys and interaction statistics useful resource in taking pictures alternatives.

6. Dynamic Preference Shifts: As college students accumulate revel in, their possibilities frequently trade. To account for these transferring conduct and learning options, the device must continuously update and retrain its fashions.

7. Behavioural Data Processing: Careful feature engineering and analysis are needed to transform unprocessed learner hobby, which include clicks, scrolling, and time spent, into insightful behavioural data.

8 .Modality Detection Accuracy:
Accurately determining a learner's desired technique of mastering is vital to the system's overall performance. Continuous model validation is important due to the fact errors in figuring out desired gaining knowledge of modes can decrease engagement and comprehension degrees standard.

(iv) RELATED WORK

With the aim of enhancing how instructional platforms alter to character rookies, studies on intelligent personalised learning systems has grown fast. The principal contributions which have prompted AI-primarily based adaptive studying technology are mentioned on this phase.

Learning theories and models, adaptivity, getting to know modality variation, learner assessment, and AI-driven recommendation systems are the five essential areas of customized getting to know research. These domain names together serve as the cornerstone of successful personalisation in contemporary e-studying.

Numerous research have analysed learner statistics, including overall performance history, engagement behaviour, and assessment consequences, using system learning (ML) and deep getting to know (DL) techniques. These procedures help identify learning patterns, expect destiny performance, and advise relevant gaining knowledge of materials.

To monitor the evolution of know-how, techniques like Long Short-Term Memory (LSTM) fashions, Recurrent Neural Networks (RNNs), and Hidden Markov Models (HMMs) are typically used. Graph Neural Networks (GNNs), embedding-based models, and matrix factorisation also are utilised to enhance the relevance and accuracy of suggestions.

Although adaptive learning has been superior by using these studies, maximum of them deal with separate elements in preference to the whole gadget. Learner modelling or content recommendation are frequently addressed by means of present frameworks, but no longer each straight away. This disparity emphasises the want for a cohesive approach, like the counselled AI-Powered Personalised Learning Path Generator, which integrates actual-time comments, adaptive recommendations, and data-driven profiling right into a unmarried clever framework.

A. Theories and Models of Learning

The basis for comprehending how people select up and maintain information is furnished by learning theories. To assure efficient content material transport and student engagement, personalised gaining knowledge of environments ought to be based on these theories. Intelligent e-getting to know layout is supported via 5 predominant gaining knowledge of theories:

1.Behaviourism:
Stresses quantifiable getting to know consequences through reinforcement and repetition, with an emphasis on stimulus-reaction behaviour.

2.Cognitive:
Emphasises internal intellectual functions that enhance learner comprehension, together with reminiscence, reasoning and hassle solving.

3.ThreeConstructivism:
Encourages students to actively discover and test so as to build information Based on past revel in.

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4. Connectivism:
This method emphasises information networks, connections, and the quick glide of information with a purpose to deal with gaining knowledge of within the digital age.

5. Humanism:
Encourages self-directed purpose-setting, intrinsic motivation, and learner autonomy.

To organise individualised learning paths, educational layout models including ADDIE, Bloom's Taxonomy, Gagné's Nine Events, ARCS Model, and Merrill's Principles of Instruction have been applied. In order to boom learner motivation, those models help educators and AI structures in correctly setting up gaining knowledge of substances and matching them to cognitive levels.

B. Adaptivity

The capacity of a system to modify gaining knowledge of sports in accordance with every learner's comprehension, velocity, and overall performance is known as adaptivity. AI-powered adaptive structures customize content material in real time via utilizing predictive algorithms and statistics analysis.

To song scholar progress and forecast future performance, techniques like Knowledge Tracing (KT), Item Response Theory (IRT), and Learning Factor Analysis (LFA) are regularly employed. Learners are categorized in step with their behavior and skill degree the usage of device mastering techniques including Decision Trees, ok-Nearest Neighbors (KNN), Support Vector Machines (SVMs), and Neural Networks.

In order to offer extra centered suggestions, clustering algorithms which includes K-Means and Fuzzy C-Means further group freshmen with similar styles.

Adaptive systems make certain that every scholar takes a direction that is suitable for his or her ability degree by means of frequently assessing progress, which complements comprehension and sustains motivation.

C. Modification of the Learning Mode

Learning efficiency is elevated by way of tailoring the way content material is provided to each learner's choices. While some college students prefer interactive simulations, games, or textual content-based totally training, others learn principles better thru videos. In order to determine effective modality adaptation, latest research emphasise the importance of operating memory capability and cognitive load management. To determine desired gaining knowledge of modalities, system learning fashions examine engagement metrics consisting of time-on-assignment, scroll styles, and interaction frequency. Delivering content in the mostgreen format is made possible by combining AI-primarily based choice detection with multimedia learning principles.

D. Assessments and Learner Behavior

Continuous evaluation and behavioural evaluation are essential for a success personalisation. Adaptive systems use real-time feedback, quiz effects, and interplay analytics to evaluate learner comprehension. Learning analytics, knowledge tracing, and behavioural statistics mining are some of the strategies used to reveal learner progress. Research shows that students who engage in metacognitive evaluation—in which they mirror on their performance—are extra stimulated and analyse more. Modern AI-pushed systems additionally hire reinforcement gaining knowledge of to alter mastering paths based totally on learner responses, making sure top of the line know-how progression

E. Personalized Recommender Systems

Because they select and gift every learner with the most pertinent content material, personalized recommender structures are critical to adaptive gaining knowledge of. These structures use real-time learner facts analysis to suggest sources that in shape every learner's goals and preferred approach of studying.

Typical strategies for hints consist of:

Collaborative filtering makes content material tips by using evaluating the preferences and behavior of freshmen.

• Content-Based Filtering: This technique matches learner profiles with content material features to signify substances.

• Knowledge-Based Recommendation: Matches studying substances with instructional requirements by means of making use of area policies and structured understanding.

• Tag-Based Recommendation: Enhances the device's comprehension of learners' pastimes by way of allowing them to tag or categorize content.

• Hybrid Methods: To improve accuracy and get round constraints like records sparsity, integrate several techniques.

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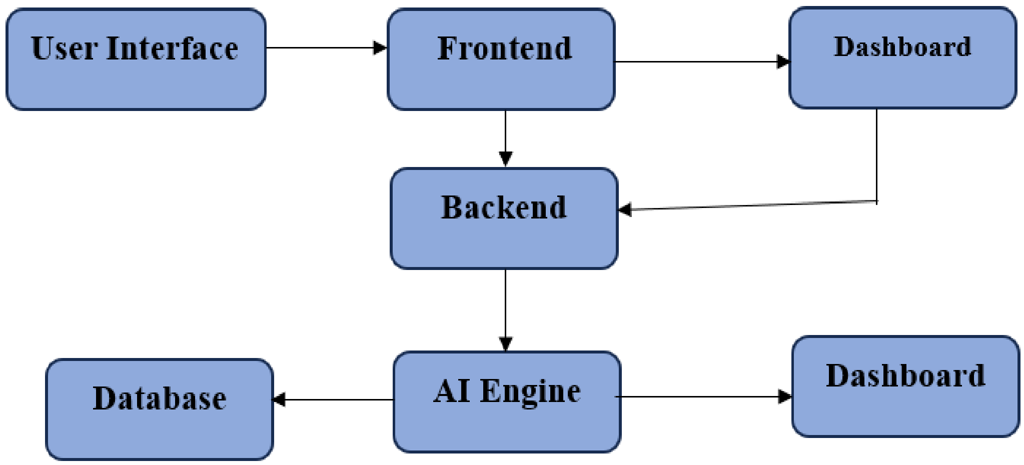

Fig 3: System architecture of the personalized learning path generator.

Recent studies has superior these systems the use of deep learning fashions like LSTM, Graph Neural Networks (GNNs), and attention mechanisms. These smart frameworks constantly adapt to converting learner behaviors, forming a comments loop that makes guidelines more accurate and simply customized through the years.

Fig 2: System workflow of AI-based personalized learning process.

(V) PROPOSED ARCHITECTURE:

The proposed AI-Powered Personalized Learning Path Generator aims to automatically create unique learning paths for students based on their progress, preferences, and performance. The system combines generative AI, machine learning, and recommendation algorithms to offer a personalized experience in real time and dynamically adjust content.

The framework uses a modern technology stack, ensuring scalability, responsiveness, and secure data handling: MySQL for the database, FastAPI for the backend, and React.js for the frontend. To support adaptive and data-driven learning, the architecture is divided into five main modules:

1. Data Module
2. Adaptive Learning Module
3. Adaptability Module
4. Recommender Module

A. Module for Data

Data Module forms the basis of the system. It records all learner statistics, such as profiles, interactions, exams, and metadata of the content. The system will generate a profile of a learner when he/she is registered and it will be updated on a regular basis depending on the patterns of activity, time spent and score of quizzes.

This data is recorded and processed to demonstrate progress and activity. The processed data is then used by other modules, particularly the Adaptive and the Recommender Modules to generate individualized learning paths and upkeep precise learner profiles.

B. Module for Adaptive Learning

The Adaptive Learning Module can assess the current understanding and learning rate of each learner using Knowledge Tracing (KT) and sequence learning models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks.

The system helps forecast the performance of a learner on the coming topics based on previous interactions and evaluation outcomes. It recognizes areas that are weak, and modifies the subsequent set of

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recommendations depending on the new mastery level of the learner on each new quiz or activity. This is to make sure that every student develops at a pace that is suitable and at the same time advancing his/her understanding.

C. Adaptability Module

Adaptability Module helps discover the favorite learning style of each learner, including interactive simulations, educational games, video watching, and reading books. It employs unsupervised learning algorithms such as clustering and association rule mining to examine the patterns of engagement in various content types such as time spent, click behavior and quiz results. Through these interactions, the system identifies the best learning mode to be used by a student and varies the manner content should be presented based on this.

D. Module for Recommenders

The Recommender Module combines the outputs of the Adaptive and Adaptability Modules in order to give individualized learning recommendations. It uses a deep learning recommendation engine that evaluates the profile of learners, performance, and preferences towards content. The system provides a list of recommended learning resources based on its analysis of the potential value of each resource. It employs different recommendation techniques, including knowledge-based, content-based and collaborative filtering, to enhance accuracy. The flexible design of the module can also be extended to incorporate in the future the reinforcement learning models to enable more flexibility.

E. Content and Assessment Delivery Module

This module serves as the interface between the AI system and students. After each activity, it collects real-time feedback and utilizes the platform to deliver suggested content and assessments.

The system can quickly update profiles and enhance recommendations since learner responses are constantly recorded and processed. This creates a smooth, adaptable learning experience whereby assessments and content are modified as the student advances. Data will be made available as it is collected and sent back to the Data. Module will assist in continuous improvements in the recommendations provided by the AI model.

This module is used to link AI system with the learner's feedback and activities. The feedback provided immediately after each activity helps in delivering the recommended material. Continuous recording of the learner's feedback helps in updating profiles and enhancing recommendations in real-time, thus creating an adaptive environment where quizzes and materials keep changing based on the advancement of learners.

Data accrued from this module will go back to the Data Module and will help the AI model

Vi) FUTURE RESEARCH DIRECTIONS

Although it can be seen that the suggested machine is capable enough to provide intelligent and adaptive learning to its users, there are still some areas which need more research and developments.

1. Generating Material Using AI: Future generations of the machine will include generative AI capabilities for generating learning material according to the requirements of individual learners.

2. Developing New Evaluation Methods: Almost all of the data being collected by existing recommendation systems is historical. Different evaluation methods should be simulated using different-learning paths.

3. Real-Time Personalization: Adaptive mastering will paintings better if real-time analytics and response times are improved. This will ensure that learners have interaction with the gadget and that customized content material is updated straight away.

4. Emotion and Engagement Detection: Using Affective Computing gear like emotion and eye-tracking analysis, we can degree learner engagement and adjust content to enhance motivation and consciousness.

5.Broader Evaluation Metrics: To offer a clearer image of gaining knowledge of effectiveness, future structures have to consist of metrics like attention time, engagement rate, and concept mastery, further to accuracy.

6.Cross-Platform Learning: Learning might be greater inclusive and available if it turns into bendy throughout net, cellular, and immersive environments (AR/VR).

7.ContinuousSelf-Learning: Reinforcement mastering can enhance personalization by using permitting the device to conform robotically to learner interactions without needing common guide updates.

(vii) CONCLUSIONS AND DISCUSSIONS

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complete, records-driven strategy integrating artificial intelligence, getting to know fashions, and real-time analytics is wanted to increase AI-powered customized getting to know structures.

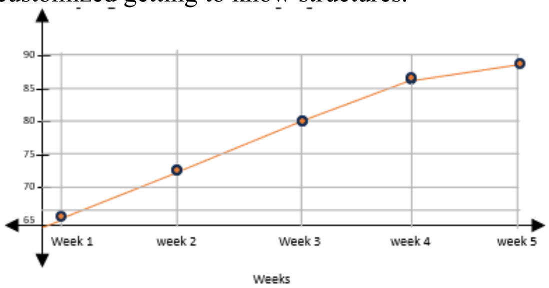

Fig 4: Learning progress trend showing improvement over session.

The AI-Powered Personalised Learning Path Generator, a framework intended to provide tailored and adaptive studying studies, become proposed on this have a look

To check learner performance, forecast progress, and dynamically modify content, the system combines device mastering, generative AI, and recommendation techniques.

Together, the structure's 5 essential modules—Data, Adaptive Learning, Adaptability, Recommender, and Content

(VIII) FORMULAS AND ALOGIRITHMS

The system calculates the user's performance percentage using a normalized scoring formula. Based on predefined thresholds, the learner is categorized into Beginner, Intermediate, or Advanced levels. The recommendation engine then filters and retrieves video resources tagged with the corresponding difficulty level.

1)User Level Detection Formula

To determine the learner's proficiency level (Beginner / Intermediate / Advanced), the system calculates a **Weighted Performance Score (WPS)** based on assessment performance.

(ii)Weighted Performance Score (WPS)

WPS=(w1×Accuracy)+(w2×CompletionRate)+(w3×AvgScore)WPS = (w_1 \times Accuracy) + (w_2 \times CompletionRate) + (w_3 \times AvgScore)WPS=(w1×Accuracy)+(w2×CompletionRate)+(w3×AvgScore)

Where:

- Accuracy = Correct Answers / Total Questions
- CompletionRate = Attempted Questions / Total Questions
- AvgScore = Average marks obtained
- w1,w2,w3w_1, w_2, w_3w1,w2,w3 = Weight values such that:

w1+w2+w3=1w_1 + w_2 + w_3 = 1w1+w2+w3=1

Example weights used:

w1=0.5,w2=0.2,w3=0.3w_1 = 0.5,\quad w_2 = 0.2,\quad w_3 = 0.3w1=0.5,w2=0.2,w3=0.3

(ii)Level Classification Rule

Level={Beginnerif WPS<0.40Intermediateif 0.40≤WPS<0.75Advancedif WPS≥0.75Level = \begin{cases} Beginner & \text{if } WPS < 0.40 \\ Intermediate & \text{if } 0.40 \le WPS < 0.75 \\ Advanced & \text{if } WPS \ge 0.75 \end{cases}Level= BeginnerIntermediateAdvanced if WPS<0.40if 0.40≤WPS<0.75if WPS≥0.75

2) Skill Score Normalization

To scale user performance between 0 and 1:

NormalizedScore=Score−MinScoreMaxScore−MinScoreNormalizedScore = \frac{Score - MinScore}{MaxScore - MinScore}NormalizedScore=MaxScore−MinScoreScore−MinScore

This ensures fair comparison across different assessments.

3) Video Recommendation Algorithm

The system uses a **Content-Based Filtering Algorithm**.

(i)Similarity Score Calculation (Cosine Similarity)

Similarity(U,V)=U·V||U||×||V||Similarity(U, V) = \frac{U \cdot V}{||U|| \times ||V||}Similarity(U,V)=||U||×||V||U·V

Where:

- U = User skill vector
- V = Video difficulty vector
- U·VU \cdot VU·V = Dot prioduct
- ||U||||U||||U|| = Magnitude of user vector

Higher similarity → Higher recommendation priority.

4) Difficulty Matching Formula

To match video difficulty with user level:

DifficultyGap=|UserLevelScore−VideoDifficultyScore|DifficultyGap = |UserLevelScore -

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VideoDifficultyScore|DifficultyGap=∣UserLevelScore−VideoDifficultyScore∣

Videos are ranked in ascending order of DifficultyGap.
Smaller gap → Better match.

5) Hybrid Recommendation Score

Final recommendation score:
FinalScore=α×Similarity+β×PopularityScoreFinalScore = \alpha \times Similarity + \beta \times PopularityScoreFinalScore=α×Similarity+β×PopularityScore

Where:

- α+β=1\alpha + \beta = 1α+β=1
- PopularityScore = (Likes + Views) / TotalInteractions

Example:
α=0.7,β=0.3\alpha = 0.7,\quad \beta = 0.3α=0.7,β=0.3

6) Algorithm: User Level Detection

Algorithm 1: Detect User Level

Input: Assessment Results
Output: User Level

1. Calculate Accuracy
2. Calculate CompletionRate
3. Calculate AvgScore
4. Compute WPS using weighted formula
5. If WPS < 0.40 → Beginner
6. Else if WPS < 0.75 → Intermediate
7. Else → Advanced
8. Return Level

7) Algorithm: Video Recommendation

Algorithm 2: Recommend Videos

Input: User Level, Skill Vector
Output: Ranked Video List

1. For each video:
   a. Compute Similarity(User, Video)
   b. Compute DifficultyGap
   c. Compute FinalScore
2. Sort videos in descending order of FinalScore
3. Return Top N videos

8) Machine Learning Model Used

The system uses:

- Logistic Regression (for level classification)
- Content-Based Filtering
- Cosine Similarity Measure
- Weighted Scoring Model

(IX) EXPERIMENTal Results and outputs.

It is thought that the system will enhance the performance of students in their learning by creating custom learning paths depending on their level of knowledge, pace of learning and performance track record.
• It will assist in the determination of weak areas of subject and prescribe befitting learning materials to enhance conceptual knowledge.

The platform will likely enhance student engagement by providing content in various formats including videos, quizzes, interactive activities, and text-based content.
Increased learner motivation and decreased boredom are anticipated to come with personalized learning experiences.
Things that the system will improve are: 1. Knowledge retention as the system will offer repeat practice and adaptive revision in hard subjects.
Real-time personalization: It is anticipated that learning paths will be dynamically modified as the learner progresses and receives feedback.

• The framework will generate the correct learner profiles through the analysis of the behavioral data such as the frequency of interactions, time spent and quiz performance.

• The system will optimize the delivery of the content, by organizing the learning materials based on the levels of difficulty, basic to advanced.

• The platform will be capable of supporting scalability and accessibility to various devices enabling flexible learning.And some of the expected outcomes of the system include: the system is likely to minimize the total amount of time spent learning, as the system will only cover the necessary areas.

• It will offer information-based insights and analytic reports to enable teachers to track the progress of students.
• The accuracy of recommendations is likely to improve with time as machine learning algorithms are continuously improved.

There are several limitations to the proposed system, which are as follows:
Despite offering some useful personalized learning recommendations, the system has the following limitations:

(i)Limited Cross-Course Scalability

The performance of the implementation is high in selective courses. But it needs fine-tuning and expanding the datasets to be able to provide congruent accuracy in all domains.

(ii)Level Classification using Static Threshold.

Predefined score thresholds are now used to determine the user levels. Although effective, this method might not be a comprehensive measure of deeper conceptual knowledge or learning behavior pattern.

(iii)Limited Large-Scale Validation

The system has been experimented with controlled environments. There should be extensive user testing in the real world to further confirm performance and scalabilities.

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