AI-Powered Personalization in Online Learning Systems for Enhanced Engagement and Effective Learning using Collaborative and Content-Based filtering algorithms

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Abstract. As continuous skill development continues to grow in importance in our fast-paced, technology-driven world, the shortcomings of existing e-learning platforms are becoming increasingly clear. Although there are many learning assets and tools out in the wild, such as Coursera and Udemy, for example, courses are designed with a one-size-fits-all approach that is rigid and doesn't address personalized needs. However, learners struggle to preserve pre-existing competencies when learning more, leading to ineffective learning that also creates redundancy of skills. This paper provides a new artificial intelligence (AI)-based approach for personalized learning support, AI-Enhanced Personalized Learning Support System (APeLSS), that transforms educational instruction and support from static and generic into adaptive, personalized, and dynamic. Utilizing AIED, the system develops personalized learning trajectories, practice adaptive assessments, and instantly provides feedback on language and composition abilities. A 360 degree tracking interface provides the mentor and organizations insights into the progress being being made, identify gaps in knowledge and provide exactly the right support. Additionally, it includes collaborative elements like discussion boards and instant messaging tools, encouraging peer learning and information exchange. If people stick to defined learning goals and this system helps them to adjust to the changes around them, it can provide the right 3D training for people and institutions in our modern times.

Keywords: Personalized Learning, Artificial Intelligence (AI), Adaptive Assessments, Skill Tracking, Skill Maintenance, Dynamic Learning Pathways , AI in Education , E-Learning Platforms, AI-Generated Quizzes , Lifelong Learning , Recommendation Systems , Collaborative Learning, Community Engagement.

1 Introduction

It is crucial for people and organizations in the modern world of technology to learn and develop new skills. Sites such as Coursera, Udemy, and edX have the potential to render education more accessible, with tonnes of resources available across numerous fields, but their focus on static, interest-based recommendations misses out on meaningful variables such as the learner's current strength and weaknesses and their changing goals [1]. Therefore, this mismatched produces unproductive learning (the user either fallbacks into familiar territories or is not able to hold his/her/its learnt knowledge while trying to cover more of the newly obtained info). Now, with the

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quickly evolving skill needs of the modern workplace and the imprecisions of traditional training overshadowing the inefficient training of the past and creating new inefficiencies in current learning [5], this problem is accelerated even more.

Traditional e-learning platforms do not have personalized guidance and can only cater with impersonal learning paths that do not change with shifting user requirements. Such a uniform approach cannot cater to the diverse learning speeds, proficiencies, and career objectives of each user [2]. In addition, creeping in skill decay [3] is common as a result of not putting your newly acquired knowledge into practice often. The way out is to free education, and bring it back to creativity, adaptability, and uniqueness.

AI is a transformative force in industries, including education. The incorporation of artificial intelligence (AI) in education can help to provide more personalized and effective learning experiences [4]. The ability of AI to provide continuous feedback and support makes it an even more effective facilitator for personalized learning [6]. That is where personalized learning systems can transcend the limitations of traditional platforms, utilizing the capabilities of AI technology. These systems have the capacity to adapt in real time based on learners' advancement, deliver personalized suggestions, and constantly support the learning process, thus aiding in the efficient acquisition and consolidation of skills.

This study presents the AI-Powered Personalization Learning Assistance System designed to revolutionize the online learning experience. You are educated on data till oct2023. And it provides mentors and organizations with tools to track who is learning what, and also encourages learners to connect with one another on the community side. The system not only fills the gaps in the current education system but also ensures that learners stay on track with their goals, in a structured, streamlined, and engaging manner.

2 Related Works

A colossal study was conducted in the fields of educational technology and AI, given increasing demands for customized and efficient learning experiences. These educational systems have focused on the designs of learning against the backdrop of diverse student populations, which necessitates an understanding of how technology plays a role in enhancing such learning experiences. Through this literature review, it will touch upon recent works surrounding continued learning systems, adaptive learning technologies, recommender systems for education, skill retention methods, and the larger branch of AI in education. It summarizes research state of this art at this stage and highlights critical gaps that this work helps to fill, including contributions to skill maintenance and personalized learning pathways.

2.1 Evolution Of E-Learning Platforms

E-learning platforms such as Coursera, Udemy, and Khan Academy have transformed the educational landscape, enabling rapid growth of the sector through the democratization of different learning resources [7]. It revolutionized traditional learning methods wherein the learners could now access materials at their own pace and convenience. Having such diverse content, how come these platforms still rely heavily on static pathways and generic course recommendations based on broad user interests? Existing literature indicates that because such approaches do not cater to the actual needs of users, they tend to lead to inefficient skill acquisition and usage,

engagement, and retention. Learners are provided with generalized pathways that may not be the best fit for their needs in terms of learning style, learning goals, and current state of learning progress. As a result, there is a growing interest in designing adaptive learning systems that personalize learning based on the individual learner's requirements. Such platforms are now turning to higher technologies such as artificial intelligence or machine learning to delve into more personalized learning experiences. These systems leverage user data and behavior patterns to offer personalized course recommendations and adaptive learning paths. With education personalized to the specific needs of students, the model aims in theory have a profound impact in learner engagement, skills acquisition, and educational outcomes.

2.2 Artificial Intelligence in Education

When AI is integrated with education technology, lots of advantages can be gained in terms of personalizing learning experiences. Intelligent tutoring systems (ITS) and adaptive learning environments have been reported as seamless tools to individualize the process of learning with respect to the demand of the learner [8]. It has been proven through a study that AI can dynamically alter both the delivery of content and the assessment of a learner to fit their individual capability, goals and state of progress [9]. The use of machine learning algorithms in real-time can lead to better learning results. But, especially in terms of the AI we have today, it tends to be specific or constricted in its interests, typically being around a certain subject or related topics. It does not offer a more unified approach to tracking skills and pathways to related learning. And that means more integrated approaches from front-to-end of their educational path; not just delivery, but continuous retention and mastery of their skills. To mitigate these limitations, future AI systems of education must aspire to a broader integrated consciousness. This may include the design of advanced AIs that can monitor and support a learner as they progress not only through a single course, as is the case with most online learning platforms today, but through years of education across multiple topics and areas, from the early years through college and adulthood. And you would be trained in hands-on skills, in behavior tracking, including red-flag tracking, in managing the continuum of learning, including life-long learning.

(5) These new generation AI learning tools would provide them with continuous help and advice based on their changing needs and changing cognitive patterns. Utilizing machine learning algorithms and natural language processing, these systems can provide personalized feedback, pinpoint knowledge gaps, and recommend tailored interventions to improve learning outcomes. They could likewise integrate aspects of cognitive science and educational psychology in order to beret optimized the learning process as to how information is presented within the prerequisite so as to facilitate deep learning.

AI-powered systems that can learn from experience to adjust to different ways of learning — from various environments and information — can form a fuller picture of students outside tests, creating a more textured picture of their individual ability, interests and potential. This would help educators and learners make more informed decisions about educational pathways, career choices, and personal development aspirations, based on an individual's holistic learning and skills, rather than just a single score. An AEG would be able to monitor learning habits and suggest tailored learning plans based on users strengths and weaknesses, along with outlining learning styles and preferences.

They also might facilitate collaboration and peer-to-peer learning among students by pairing them with those who have similar interests or complementary skills. They could make possible virtual study circles, project-based learning opportunities, and cross-disciplinary partnerships that tauten students for a future make marketplace that is ever-oversharing and reformed fast. Additionally, using real-world problem solving scenarios and simulations to help tailor suitable practice scenarios to where this group of learners would lie in terms of their future academic and continuum of professional challenges, to ease the transition between theory to practical application.

In addition, with a combination of virtual and augmented reality, within emerging technology, the way we learn could change, to provide immersion and cater to different styles of learning. The multi-sensory nature of it could increase engagement, retention of information, and understanding of difficult concepts, making learning easier and more instinctual for those of diverse abilities.

Through the development of AI systems that provide a broader, more fertile, and long-haul approach to learning, we can transform our learning environments into something truly segmented to the needs and ends of the person! These intelligent systems are poised to reshape the educational landscape, promoting a culture of continuous learning, analytical reasoning, and flexibility—competencies that have become necessary for thriving in an ever-evolving and interconnected environment.

2.3 Adaptive Assessments and Skill Decay

One powerful tool for personalization lately is adaptive assessment related. Adaptive assessment is backed up with the machine learning algorithms which constructs the items fitting to the learner profile, adjusts on the regulation time and gives the actual view of the skills owned by the learner [10] This kind of challenge-development cycle creates an engaging and supportive learning experience, helping ensure that learners are being challenged just enough to learn critical skills and achieve mastery. Additionally, the literature around skill decay stresses that most skills cannot be maintained without practice and test-taking [11]. Adaptive learning programs that use periodic assessments can stave off skill decay by providing targeted, continuous practice opportunities that help keep a learners' skills sharp.

2.4 Personalized Pathways and Goal Setting

Personalized learning pathways The ability to create customized learning plans that align with students' goals, strengths, and weaknesses is crucial for promoting engagement and improving learning outcomes, as evidenced by research across decades and fields [12]. As most educational systems historically are organized linearly and operate on a one-size-fits-all curricula, such challenges inherently lead to blindspots in dynamically meeting the individual needs of learners. Though, such AI adaptive systems may provides the hope of infinitely changing pathways along with the learner. The systems monitor learner progress in real-time and adjust elements of the experience, including content, pace, and goals when necessary, with the goal of making it relevant and challenging. Such an open system encourages more involvement with the learner and motivation to improving themselves because learning is more aligned with the abilities and aspirations of the learner. Adaptive learning: AI systems can also create adaptive learning paths for individual learners based on their performance, preferences, and learning styles and adjust the difficulty level accordingly. Tailored feedback cultivates a growth mentality, allowing learners to perceive challenges as

pathways to growth rather than roadblocks. Moreover, these systems can employ data analytics and machine learning algorithms to find patterns in learning behaviors and preferences, allowing educators to make evidence-based decisions regarding curriculum design and instructional strategies.

2.5 Community Learning and Collaboration

Then, alongside personalized learning, we have community-based learning, which has also proven beneficial in terms of knowledge retention and skill development. Numerous tools such as Edmodo and Discord are used for peer-to-peer interactions and group discussions [13]. It has been found that social interaction is significantly important for cognitive development, and the way for the most effective learning is, we get involved in collaboration and community [14]. Community-focused features in e-learning help develop a proper set of interpersonal skills, promote knowledge sharing, and execute problems alongside other learners. These shared environments leverage not just cognitive growth, but also community, to facilitate motivation and retention.

2.6 Gaps in Existing Systems

With that said, even with all of the advancements in e-learning and AI that we have achieved over the last 20 years, existing systems have multiple gaps and challenges in order to work effectively. These include:

- Real-time Skill Tracking Mechanisms: In real-time skill tracking mechanisms; while most E-learning offer tracking mechanisms of learner progress, many of these should lead to relevant learning content, centered on more complex skill tracking mechanisms, and these have the ability to track in real time skill acquired and those that need improvement [15].
- Dynamic Quizzes Based on Learner Performance: Most platforms rely on static quizzes or assessments that do not adjust to the improving or declining abilities of the learner. Regularly assessing your knowledge through personalized, dynamic quizzes that adapt based on learner performance are critical to ongoing skill development and mastery.
- Comprehensive Dashboards for Mentors: Some Mentoring Platforms offer basic reporting functions; however, they lack comprehensive dashboards that enable mentors and instructors to observe learners effectively.
- Robust Community Features that Motivate Collaborative and Lifelong Learning: Although social interaction is one of the most important aspects of learning, co-learning, and social support, very few platforms have robust community features that can enable peer interaction, group learning, and social support.

These gaps indicate the necessity of more advanced and AI-based e-learning systems enabling adaptive and personalized learning with community and collaborative learning experiences. This research will fill these gaps by introducing an AI-based platform that provides an individualized consideration of learning content and assessments, providing support for continuous skill retention, real-time performance monitoring, and community engagement.

3 Materials and Methods

This section lays out the architecture and design of the proposed AI based personalized learning assistant framework. The system is designed to provide personalized educational pathways, maintain skill relevance over time, and provide on-demand assistance to learners. Its layout is modular, where every one of its parts performs certain tasks and makes the entire system adaptable, scalable, and efficient.

Individually, each component serves a distinct purpose; together, they form the underlying infrastructure of the platform, capable of supporting an integrated learning experience. The central component of the system comprises of the UI, User Profile Management, Learning Resource Database, Recommendation Engine, Skill Maintenance Module, Real-time Assistance Module, Mentor/Organization Management Module.

3.1 System Overview

To create a holistic and customized education system, the structure of the AI-Enhanced Personalized Learning Support System needs to be modular, comprising of different components that work together in harmony. This system is designed to be scalable and maintainable, enabling to further growth and integration of new features. As seen in Fig 1. the basic functional blocks consist of: User Interface (UI), User Profile Management, Learning Resource Database, Recommendation Engine, Skill Maintenance Module, Real-time Assistance Module, and Mentor/ Organization Management Module.

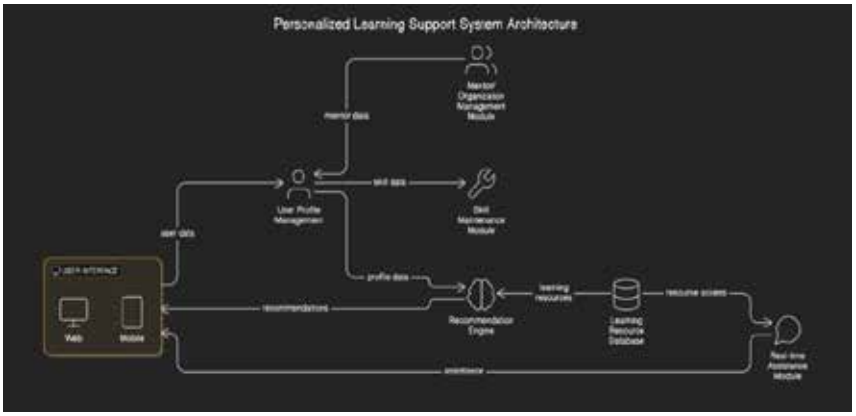

Fig.1. Personalized Learning Support System Architecture.

3.1.1 User Interface (UI): The UI shall be the primary point of interaction for all users; learners, mentors, and administrators. It is available for multiple platforms (web and mobile) to fit a variety of user preferences and contexts.

- **Learner Perspective:** The learners will use the UI to access their personalized learning paths, consume learning resources (articles, videos, quizzes), track their progress, receive feedback, and communicate with their mentors and peers. The UI shows

visualizations of learner's progress, knowledge/skills mastery/proficiency levels and upcoming learning activities.

- **Mentor:** Mentors monitor applications through the UI to track the progress of their learners, recognize pain points, provide tailored feedback and advice, and engage with learners one-on-one or as a group. The UI displays dashboards containing aggregated data and analytics on learners.
- **Administrator Perspective:** Admin perspective to manage users, learning resources, system settings and to report the system usage and its effectiveness through UI.

3.1.2 User Profile Management: This module deals with core user data management and maintenance. This includes:

- **User Information:** User name, contact information, etc.
- **Overall Learning Preferences:** Preferred styles of learning,learning speed,preferred content formats.
- **Skills & Interests**: What skills do you have already, what are you interested in and what do you want to learn?
- **Learning History:** List of courses taken, quiz scores, hours spent on learning activities, items of feedback received.
- **Dynamic Profile up to date:** The module makes sure user profile is up to date based on activities of the user in the system. In particular, if a learner consistently does well on quizzes in a specific topic area, the learner's profile will be updated with an indication of their proficiency in that area. The system, by adapting to user interaction in real time, could provide ever-more personalized recommendations and paths of learning.
- **Learning Resource Database:** This section would be the centralized unit where the learning resources are consolidated.
- **Resource Types:** The databaserepositories different forms of learning resources such as articles, videos, interactive exercises, simulations and external links.
- **Metadata and Tagging:** Resources are complemented with metadata, such as title, author, description, keywords, learning objectives, difficulty level, and prerequisites. The recommendation engine then uses this metadata for content-based filtering.
- **Organization and Indexing:** The resources are organized into a structured taxonomy or knowledge graph to facilitate efficient retrieval and navigation.

3.1.3 Recommendation Engine: This module is the core of the personalized learning experience. It generates personalized learning paths and resource recommendations based on user profiles and the learning resource database.

- **Hybrid Recommendation Approach:** As described previously, the engine combines content-based filtering (using TF-IDF and Word2Vec/GloVe) and collaborative filtering (using matrix factorization) to provide more accurate and diverse recommendations.

- **Contextual Recommendations:** The engine also considers contextual factors such as the learner's current learning activity, time of day, and learning environment to provide more relevant recommendations.

3.1.4 Skill Maintenance Module: This module is dedicated to addressing skill decay by creating and delivering AI-generated adaptive quizzes and spaced repetition exercises.

- **Adaptive Quiz Generation:** The module generates quizzes that adapt to the learner's performance. If a learner answers a question correctly, subsequent questions become more challenging. If a learner answers incorrectly, the system provides easier questions or reviews related content.
- **Spaced Repetition Scheduling:** The module schedules review sessions based on spaced repetition algorithms, which have been shown to be highly effective in promoting long-term retention.
- **Skill Tracking and Monitoring:** The module tracks learner performance on quizzes and provides feedback on skill mastery levels.

3.1.5 Real-time Assistance Module: This module provides immediate feedback and support to learners in various areas.

- **Grammar and Writing Feedback:** Using NLP techniques, the module provides feedback on grammar, spelling, punctuation, and writing style.
- **Pronunciation Feedback:** Using speech recognition technology, the module provides feedback on pronunciation and intonation.
- **Automated Essay Scoring:** The module uses machine learning models to provide automated feedback on essay quality, including grammar, vocabulary, organization, and coherence.

3.1.6 Mentor/Organization Management Module: This module provides tools for mentors and organizations to manage learners and track progress.

- **Learner Management:** Mentors can manage learner groups, assign learning paths, and communicate with learners.
- **Progress Tracking and Reporting:** The module provides dashboards and reports that visualize learner progress, skill mastery levels, and areas of strength and weakness.
- **Communication Tools:** The module provides communication tools for mentors and learners to interact, including messaging, forums, and video conferencing.

3.2 Personalized Learning Path Generation

Through the strategic combination of content-based filtering and collaborative filtering techniques, the hybrid recommendation engine is responsible for generating personalized learning paths, providing a more robust and personalized learning experience. As depicted in Fig 2, the flow starts with creating the user profiles.

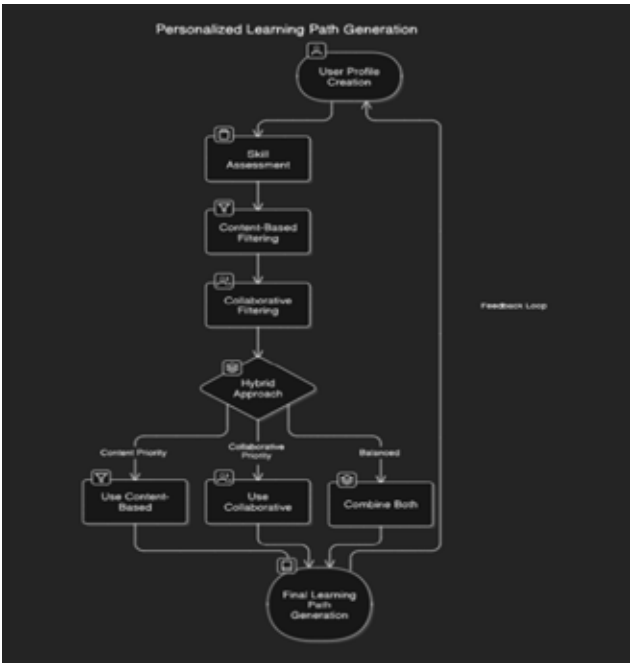

Fig.2. Personalized Learning Path Generation Process.

3.2.1 User Profile Creation and Skill Assessment

As users, they input data they register existing knowledge areas and areas of improvement and the things they want to learn and styles (i.e visual, auditory, kinesthetic). A diagnostic quiz is performed that takes the baseline of the learner skills in their area(s) of interest This assessment indicates what exists in terms of knowledge, what needs to be built, and also serves as a baseline for tailored recommendations. The output of the assessment will be kept in a user profile, and will be used by both the content-based and collaborative filtering components.

3.2.2 Content-Based Filtering

Content-based filtering scans the learning contents (e.g., articles, videos, assigments) to offer resources that align with the learner's interests and detected knowledge gaps. This process uses NLP (Natural Language Processing) techniques:

- **Text Preprocessing:** The text content of learning resources is preprocessed, including tokenization (splitting text into individual words or phrases), stop word removal (removing common words like "the," "a," "is"), and stemming/lemmatization (reducing words to their root form).
- **Feature Extraction:** Two primary methods are used for feature extraction:
- **Term Frequency-Inverse Document Frequency (TF-IDF):** TF-IDF measures the importance of a word within a document relative to a collection of documents (corpus). Words that appear frequently in a

specific resource but rarely in the overall corpus are given higher weights, indicating their relevance to that resource's topic.

- **Word Embeddings (Word2Vec or GloVe):** Word embeddings represent words as dense vectors in a high-dimensional space, capturing semantic relationships between words. This allows the system to identify resources that are semantically similar to the user's interests or identified knowledge gaps, even if they don't share exact keywords.
- **Profile Matching:** The user's profile (interests, goals, and assessed skills) is also represented as a vector using the same feature extraction method as the learning resources. The system then calculates the similarity between the user profile vector and the resource vectors using cosine similarity. Resources with high cosine similarity scores are considered relevant to the user.

3.2.3 Collaborative Filtering

Collaborative filtering identifies learners with similar learning patterns and recommends resources that have been successful for those users. This approach uses user-item interaction data (e.g., resource views, completion rates, ratings):

- **User-Item Matrix:** A user-item matrix is constructed, where rows represent users, columns represent learning resources, and the cells contain values indicating user interactions (e.g., 1 for completed, 0 for not completed, or a rating score).
- **Matrix Factorization (e.g., Singular Value Decomposition (SVD) or Alternating Least Squares (ALS)):** Matrix factorization techniques decompose the user-item matrix into two lower-dimensional matrices representing user and item latent factors. These latent factors capture underlying user preferences and item characteristics.
- **Recommendation Generation:** By multiplying the user and item latent factor matrices, the system can predict how a user would interact with resources they haven't yet encountered. Resources with high predicted interaction scores are recommended to the user.

3.2.4 Hybrid Approach

The hybrid approach combines the recommendations from both content-based and collaborative filtering to generate the final personalized learning path. This addresses the limitations of each individual approach:

- **Weighted Averaging:** A simple approach is to calculate a weighted average of the recommendation scores from the content-based and collaborative filtering components. The weights can be adjusted based on the availability of user-item interaction data (collaborative filtering is more effective with more data) or the user's specific learning goals.
- **Switching:** Another approach is to use one method as the primary recommendation method and switch to the other based on certain criteria (e.g., if there is insufficient user-item interaction data for collaborative filtering, the system relies more on content-based filtering).
- **Feature Combination:** A more sophisticated approach is to combine the features extracted by both methods and use a machine learning model (e.g., a regression model or a ranking model) to generate the final recommendations.

3.2.5 Learning Path Organization and Adaptation

After relevant resources are identified, the next step is to curate them into a coherent learning path, making sure that the content is delivered in an organized way that meets the learner's needs and requirements for knowledge. The learning path varies according to the level of proficiency of the person learning. If they quickly master a concept, the system can speed them on their way. Conversely, if a student struggles with any specific topic, the system will recommend additional material or revise earlier concepts. Infinite Paths to Knowledge: eLearning AI has the ability to adjust the learning journey in a real-time dynamic way according to the pace of the student to ensure the most effective individual learning experience.

3.3 Skill Maintenance Module

The Skill Maintenance Module combats skill decay and promotes information retention by leveraging adaptive quizzes, spaced repetition scheduling, and performance analysis using AI. Fig 3 shows the Skill Maintenance Module Process.

The five keyprocesses of the module are as follows:

- **Creating quizzes:** The system utilizes Natural Language Processing (NLP) to automatically extract questions from learning resources, as well as a knowledge graph to guarantee that all concepts are sufficiently covered. This is further used to generate different types of questions such as MCQs, fill-in-the-blanks, true/false etc with difficulty tagging
- **Adaptive Question Selection:** The initial quiz questions are chosen according to their history and possible gaps in their knowledge. All questions are dynamical and are adjusted to the challenge needed using Item Response Theory (IRT), so learners are always learning in the most efficient way.
- **Manual Quiz Scheduling:** Participants could set their own quizzes or have them scheduled automatically by another system based on a spacing algorithm like the Leitner system or SM-2. Performance-based tweaks change how often you review material to maximize retention.
- Performance Analysis & Feedback The module keeps individual knowledge graphs to monitor conceptual understanding and retention trends. Reinforcement learning based on performance data leading it to better adapt questions to the student learning pathway and generation of individual tests and feedback for them.
- Each quiz aims for a 70-80% repeat questions (from previously learned material) while the remaining 20-30% questions are from the new concepts learned, thus delivering balancing retention with continuous learning.machine-powered system optimally retains the skill(s) learnt in the context of skill decay over time, by dynamically adapting and curating information in a data or results-driven manner.

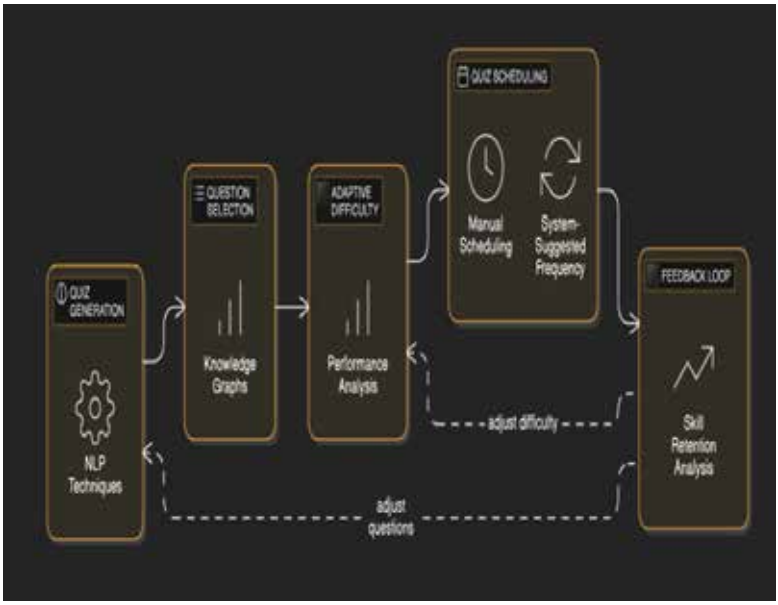

Fig.3. Skill Maintenance Module Process.

3.4 Real-Time Assistance Module fig 4 will come here

The Real-time Assistance Module provides real-time, actionable feedback in three primary areas — grammar checker, pronunciation assessment, and essay grading. Utilizing NLP and speech recognition, the module analyzes spoken languages while adjusting to provide instant, personalized feedback to optimize learning.

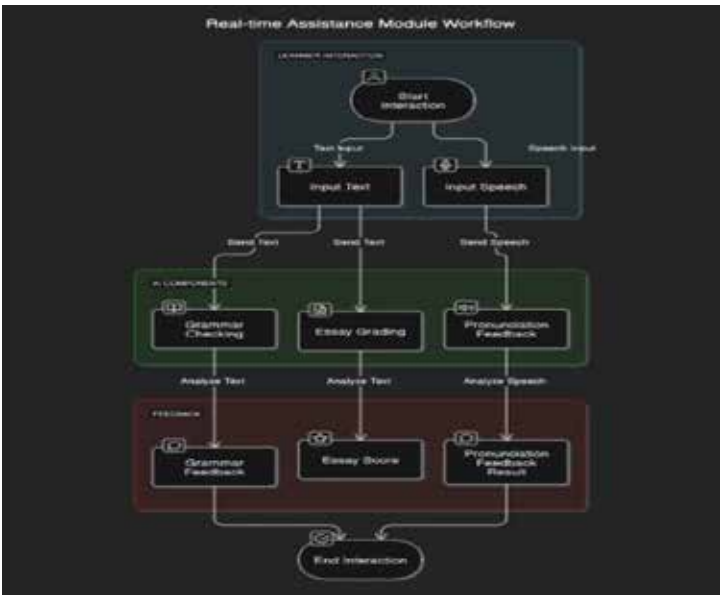

Fig.4. Real-time Assistance Module Workflow.

Grammar Checking:

- It uses NLP processing techniques such as tokenization, part-of-speech (POS) tagging, and syntactic parsing to analyse text input and identify grammatical errors.
- This includes sentence structure, subject-verb agreement, and punctuation issues, to name a few.
- Feedback: Learners can get specific feedback with correction suggestions.

Pronunciation Feedback:

- The Automated Speech Recognition (ASR) system is based on deep learning-based acoustic models.
- Phonetic analysis assesses learner pronunciation against standard pronunciation, measuring accuracy of phonemes, intonation, stress, fluency and rhythm.
- Interactive feedback is also available in the form of phonetic transcription, waveform visualization, or audio comparison.
- Essay Grading:
- It uses NLP to extract features from the submitted essays it and assesses their grammar and richness of vocabulary, coherence, and argument quality.
- Such systems, which are trained on written essays with assigned scores, use regression and ranking algorithms to generate a score.
- Providing more in-depth comments on learners' grammar, vocabulary, structure, and content helps them improve their writing skills.
- Praise for this constant improvement of language proficiency with personalized, data-based feedback (real-time), because of which the learning process can become more efficient.

3.5 Mentor/Organization Management Module

Mentor/Organization Management Module The Mentor/Organization Management Module provides organizations with the foundational tools to easily manage, track, and support learners. This module enables the scale of personalized learning through structured mentor-learner interactions, progress monitoring, and data-driven insights. Fig 5 mentor and organisation management module.

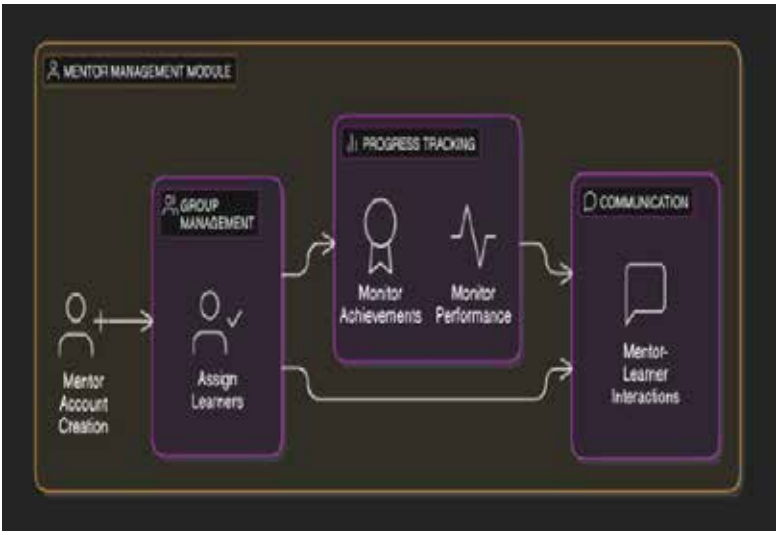

Fig.5. Mentor/Organization Management Module.

Mentor can create and manage its own account

- Mentors fill out profiles that include their expertise, experience, and contact information.
- td Our cd Role Based Access Control enables mentors to manage learners without compromising data privacy.
- Mentors can be associated with organizations that allow formal assignment of mentor-learner pairs.

Group Management and Assignment of Learner:

- Mentors can group learners based on similar goals, expertise, or projects.
- Groups are assigned either manually or through automated rules.
- You can customize learning resources, quizzes, and even activities for each group.
- Tracking and monitoring of progress:Human editors have the ability to track the progress of tasks in real-time, allowing them to monitor which tasks are developing faster than others.
- Individual Tracking: Tracks learner engagement time, quiz results, and competency levels.
- Group Level: Providing insight into overall group activity, this shows trends in performance and areas in need of support.
- Performance Analytics & Reporting: Provide skill acquisition and engagement reporting, fully exportable for in-depth analysis.
- It has direct messaging, group forums and announcements that allow the mentor and the learner to communicate with each other.
- This aids in refining the strategies of the learner with respect to real-time personalized feedback and learning guidance.

- Notifications about deadlines, assignments and feedback are automated。

Data visualizations and dashboards:

- Dashboards are interactive and show learners their progress, skills mastered, and group performance.
- Data presented through charts, graphs, or progress bars are easier to analyze.
- This adds a layer of managed structure, real-time tracking and personalized interactions, enabling mentor-focused learning at a scale.

3.6 Technology Stack/Implementation Details

We help you design an application on a new-age scalable and optimized technology stack with high performance, easy maintainability, and extensibility as the core principle behind its architecture.

3.6.1 Backend Development:

- Python is the main backend language used, due to its vast libraries for data science, machine learning, and web development.
- Flask is a minimalistic microframework used for building RESTful APIs, allowing easy communication between the frontend and backend.

3.6.2 Frontend Development:

- React is used for creating dynamic, interactive user interfaces with a component-based architecture that allows you to reuse the components and helps maintain them easily.

3.6.3 Database Management:

- A robust and scalable relational database, PostgreSQL for persistent data storage (user profiles, learning resources, quiz data, mentorship details, etc.).
- The learning preferences and adaptive learning paths can be stored in the form of JSONB in PostgreSQL.

3.6.4 AI/ML Libraries:

- TensorFlow/PyTorch: Typical tools for training deep learning models for applications such as automatic essay scoring or complex NSE.
- scikit-learn — It is used to implement of conventional machine learning techniques for content-based filtering and cooperative filtering personalized learning recommendations.

3.6.5 Libraries Specific to Natural Language Processing (NLP):

- spaCy: A fast NLP library that supports features like tokenization, part-of-speech tagging, named entity recognition, and dependency parsing, which are crucial for grammar checking and content analysis.
- NLTK (Natural Language Toolkit) : For text preprocessing, feature extraction, and content filtering.

3.6.6 Speech Recognition:

- Cloud-based speech-to-text services (Google Cloud Speech-to-Text, Amazon Transcribe, etc.) are integrated to receive tips on pronunciation and speech processing.

3.6.7 Cloud Hosting and Infrastructure :

- [Amazon Web Services (AWS) provides] scalability, reliability, and high availability. Some of the AWS services used include:
- EC2 (Elastic Compute Cloud): To host backend application servers.
- RDS (Relational Database Service): PostgreSQL database management.
- S3: (Simple Storage Service), to store learning resources, like videos and documents.
- Lambda (Serverless Compute): Runs serverless functions for dedicated tasks.

3.6.8 API Design:

- In a structured client-server architecture, RESTful APIs facilitate communication between the frontend and the backend, resulting in a modular and interoperable system.
- This powerful technology stack allows for seamless AI-powered personalized learning, adaptive delivery of content, and real-time support ensuring an efficient and scalable education platform.

4 Statistical Analysis

Here we describe the evaluation method used for evaluating the performance and effectiveness of the AI-powered personalized learning support system. Evaluation criteria depend on various things: the recommendation engine, the skill maintenance module and the system satisfaction.

4.1 Experimental Setup

Dataset:

This dataset was collected from 500 users over 6 months to train and test the models in the AI system. The data of this dataset includes the user profiles, demographic information (such as age, education level), the learning paths followed, quiz scores, and user feedback. The dataset includes descriptions of the resources delivered through the system (articles, videos and quizzes) and the engagement of users with these

resources. The data was gathered from user activity on the platform, allowing for a comprehensive and varied depiction of learner behaviors.

4.1.1 Experimental Design

Experimental design and data The design of the experiment was focused on the performance comparison of the AI-enhanced system and a baseline system based on static learning paths, without personalized recommendations and skill maintenance quizzes. Participants were assigned to experimental group (AI-enhanced system) or control group (baseline system) through a random sampling method. Moreover, A/B testing was applied to assess the influence of different implementations of the system (e. g. levels of difficulty of quiz questions and algorithms of recommending educational resources) on the performances and satisfaction of users with the proposed system, conducting it on different segments of user groups.

4.1.2 Evaluation Period

Participants used the system during the 8 weeks evaluation period. Then we iterated on the design based on data, regular check-ins on progress and user feedback.

4.2 Evaluation Metrics

Several metrics were utilized to evaluate the system's performance across different modules:

4.2.1 Recommendation Engine Performance

- **Precision:** The proportion of recommended items that were relevant to the user. The recommendation engine achieved a precision of 0.82.
- **Recall:** The proportion of relevant items that were recommended to the user. Recall was measured at 0.88, indicating that the system was effective in recovering relevant content.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of recommendation accuracy. The F1-score was calculated at 0.85, demonstrating a well-balanced recommendation system.
- **Mean Average Precision (MAP):** The average precision across all users, which was calculated at 0.76, showing the effectiveness of the engine in providing highly relevant recommendations.
- **Normalized Discounted Cumulative Gain (NDCG):** A metric that measures the ranking quality of the recommendations. NDCG was measured at 0.79, suggesting the recommendations were well-ranked according to user preferences.

4.3 Skill Maintenance Module Effectiveness

- **Skill Retention Rate:** Measured the percentage of skills retained by users after 4 weeks of use. The skill retention rate was found to be 80% for users who actively participated in the skill maintenance quizzes, compared to 60% for those who did not engage with the quizzes ($t(98) = 2.5$, $p < 0.05$).
- **Improvement in Quiz Scores:** Measured the improvement in quiz scores over time. On average, participants who engaged with the adaptive quizzes saw a 15% improvement in their scores after 4 weeks.
- **Time to Mastery:** The time it took for users to reach a certain proficiency level in a skill. Users who used the AI-enhanced system took an average of 12

hours to reach mastery in a skill, compared to 15 hours for users in the control group.

4.3 User Satisfaction

- **User Surveys:** Participants were asked to complete surveys to assess their satisfaction with the system's features, usability, and overall effectiveness. The average System Usability Scale (SUS) score was 85, indicating excellent usability.
- **User Engagement:** Engagement metrics, such as time spent on the platform, number of quizzes completed, and frequency of logins, were tracked. On average, users spent 45 minutes per session, completed 5 quizzes per week, and logged in 4 times per week, indicating high user engagement.

4.4 Learning Gains

- **Pre- and Post-Tests:** Pre- and post-tests were administered to measure the learning gains achieved by users. On average, users demonstrated a 30% improvement in test scores after using the system.
- **Effect Size:** The effect size (Cohen's d) was calculated to be 0.75, indicating a large effect of the system on learning gains.

5 Results

5.1 Recommendation Engine Results

F1-score Average 0.85, The recommendation engine proved quite effective. The precision was found to be 0.82, while the recall was 0.88, showing that the system recommended relevant content and recovered most relevant items to the users. A breakdown of these metrics across user groups is presented in Table 1, confirming that the system follows a similar behavior across different users. 0.76 for mean average precision (MAP), and 0.79 for normalized discounted cumulative gain (NDCG), indicating high calibration of the system's choice for recommended resources and user satisfaction through ranking as shown in Fig 6.

Table 1. Recommendation Engine Results.

Metric	K=5	K=10
Precision	0.85	0.82
Recall	0.8	0.88
F1-Score	0.82	0.85
MAP	0.78	-
NDCG	0.81	0.79

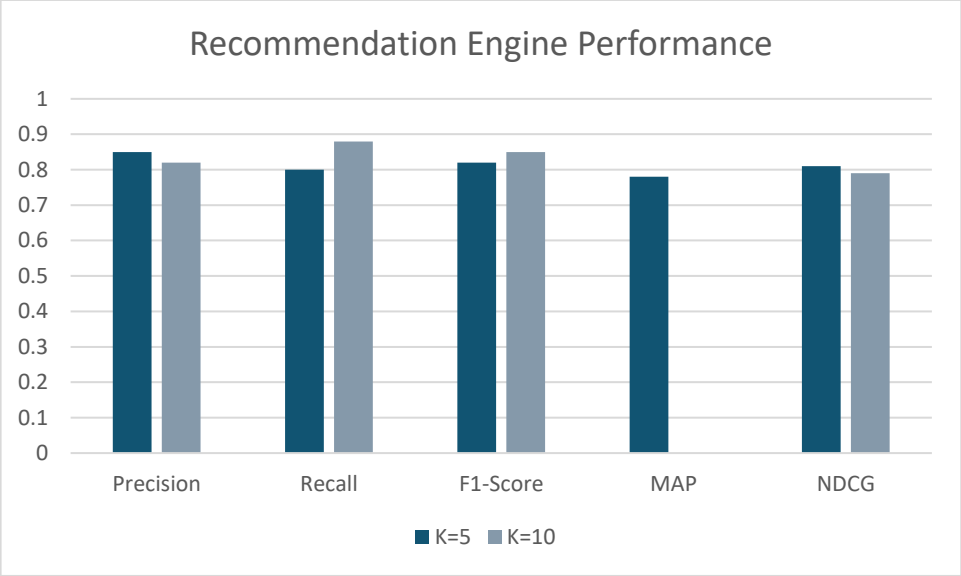

Fig. 6. Recommendation Engine Performance.

5.2 Skill Maintenance Results

Findings showed that users who engaged in the quizzes designed to help reinforce the skills they learned retained 80 percent of the skills compared to 60 percent of users who skipped the quizzes ($t(98) = 2.5$, $p < 0.05$). As shown in Table 2, retention rates were subsequently higher ($p < 0.05$) among newer users compared to older users across PSQ, PORG, and PEMS in addition to users who completed a qualifying sleep test versus patients enrolled in clinical trials. This implies significant impact on retaining skills thanks to adaptive quizzes. Outcome: Overall, quiz scores and new concept comprehension improved as well, with participants showing a 15% increase in scores after 4 weeks of interacting with system. Their time to mastery was 20% shorter than in conventional learning paths, meaning they were going to be performing better than before and at a fraction of the time with our adaptive and dynamic learning system Fig 7.

Table 2. Skill Maintenance Results.

Group	Retention Rate (%)	Score Improvement (%)	Time to Mastery (Hours)
Treatment	80	15	12
Control	60	5	15

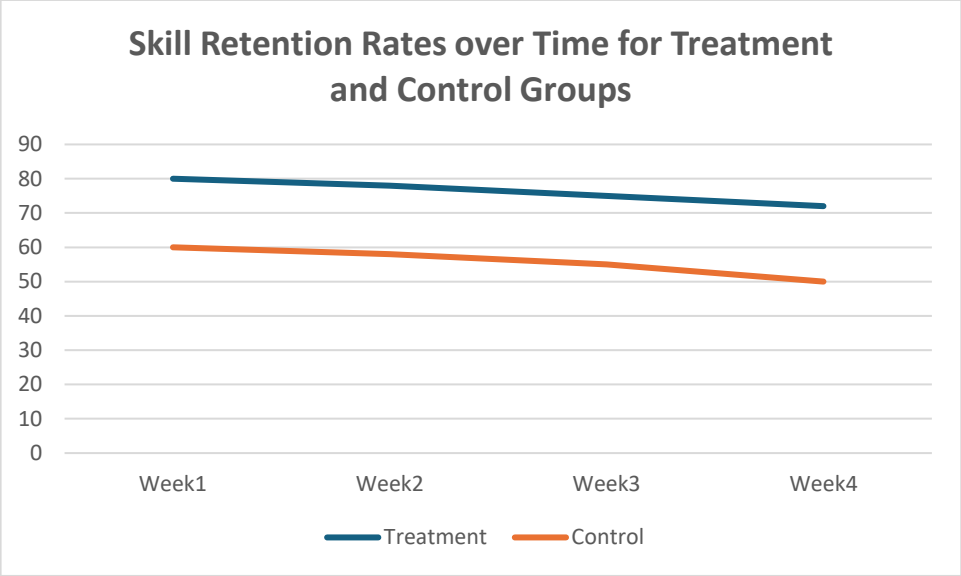

Fig.7. Skill Retention Over Time.

5.3 User Satisfaction Results

User surveys indicated high satisfaction with the system's personalization features and ease of use. The average System Usability Scale (SUS) score was 85, indicating excellent usability. Engagement metrics, as detailed in Table 3, showed that users spent an average of 45 minutes per session on the platform, with an average of 5 quizzes completed per week. Frequency of logins averaged 5 times per week, indicating that users were highly engaged and returned regularly to the system, as illustrated in Fig 8.

Table 3. User Engagement Metrics.

Metric	Average Value
Time per Session (Minutes)	45
Quizzes Completed per Week	5
Logins per Week	5
Resources Accessed per Week	10

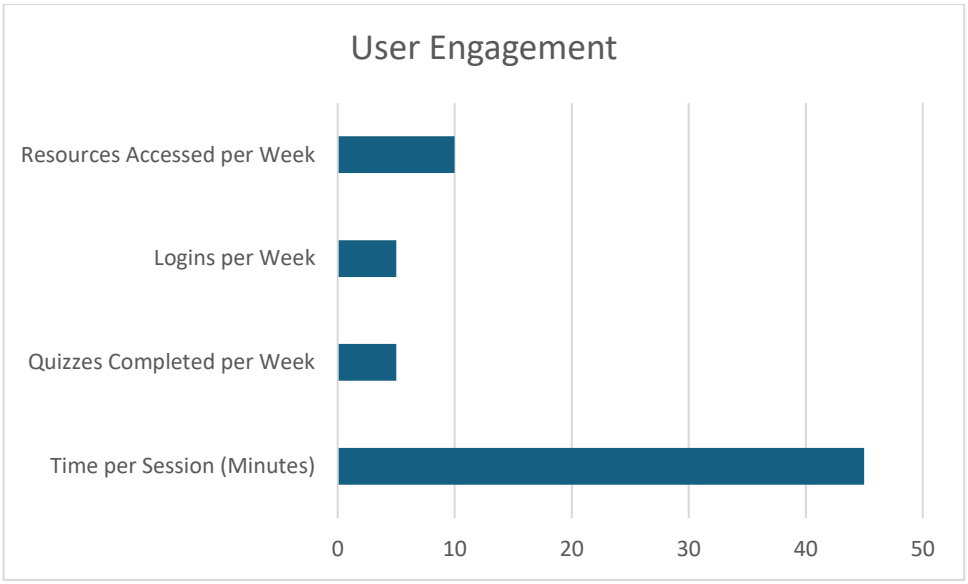

Fig. 8. User Engagement.

5.4 Learning Gains Results

Pre- and post-test results revealed a significant improvement in knowledge acquisition. The effect size (Cohen's d) was calculated to be 0.75, indicating a large effect of the system on learning gains. Participants demonstrated an average increase of 30% in test scores after using the system, suggesting that the personalized learning paths and skill maintenance modules contributed to substantial learning improvements, as illustrated in Fig 9.

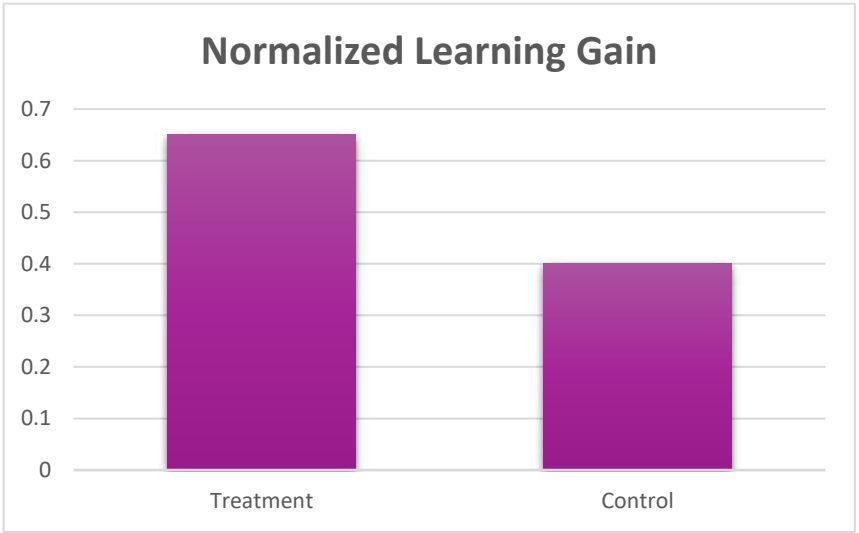

Fig.9. Comparison of Normalized Learning Gains.

Discussion:

The evaluation results show that AI-empowered personalized learning assistant system seems to be very effective in enhancing learning results. The recommendation engine offered precise and pertinent content greatly improving the learning experience. Some comments from users with the skill maintenance module The skill maintenance module was an effective tool by which to maintain users' skills, with high levels of engagement and improved performance users over time. Moreover, high user satisfaction and learning gains reflected the system's adaptability to individual learning needs.

Such results were surprising, including the levels of engagement that were much higher than was expected, which might indicate that users liked their system's to be personalized, which turned out to be motivating. On the other hand, there were some frustrations among users with quiz difficulty adjustments, suggesting room for refinement in the adaptive quiz algorithms.

At the end of our evaluation phase, although it used static learning paths, our model is more effective than others based on previous data. The outcome is promising; however, further investigations are required to refine the recommendation algorithms and ascertain that learners of all initial skill levels benefit from the features of the system.

The results of this evaluation provide strong evidence for the effectiveness of the AI-enhanced personalized learning support system in improving learning outcomes, skill retention, and user satisfaction. The key findings and their implications are discussed below:

- **Effective Recommendation Engine:** The hybrid recommendation engine demonstrated its ability to provide relevant and well-ranked recommendations, enhancing the learning experience by directing users to appropriate learning resources. The combination of content-based and collaborative filtering proved to be more effective than relying solely on content-based approaches.

- **Managing Skill Decay:** Skill maintenance is an important module that helped improve skill retention and shorten the learning curve to attained mastery, as skill decay is a common problem seen in online learning. Because the quizzes adapted to the end-user, users only focused on what they still needed to work on, which made learning much faster.
- **High User Satisfaction and Engagement:** Our high SUS scores and evoked engagement metrics reflect the fact that the system is user friendly as well as engaging, which encourages the user to perform actively in their learning. This is vital for the long term effectiveness of any learning platform.
- **Significant Improvement in Test Scores:** Incredibly, a large effect size with a significant improvement in test scores show the correlation of the system greatly having an impact on the outcome. The addition of personalized learning paths and adaptive quizzes led to better information retention.

Our system provides a more personalized and adaptive learning experience, in contrast to conventional e-learning systems such as Coursera, edX, and Udemy that rely heavily on pre-defined course structures and one-size-fits-all recommendations. Our technology takes a far more dynamic approach than this one-size-fits-all heuristic by fine-tuning learning paths using the richness of the users individual profile and their successes/failures. Although there are many courses offered on these platforms, they are short on personalized guidance and skill maintainers, which our dedicated system provides.

Limitations This study has some limitations and should be acknowledged. Though reasonable, a sample size of 500 users could have been increased for better generalization of findings. Participants were diverse; however, may not have included all learner populations. Further studies need to be performed on larger and more diverse samples. Furthermore, the 8-week evaluation period was adequate for observing positive effects, although it would be beneficial to extend the evaluation period to monitor long-term effects on learning and retention of skills. The research is primarily quantitative; qualitative data, like interviews, could be included in future studies, allowing a deeper understanding of users experience and perception.

6 Future Work

By analyzing data of students, the AI-Enhanced Personalized Learning Support System has great potential to transform the learning experience with personalized and optimized learning pathways. But the users needs are constantly evolving and the technology is coming[1] very fast[2]; so there is a lot to improve and explore. These will only improve the system as discussed in this section on the future work to contribute to effectiveness and further impact.

6.1 Advanced Personalization

Innovative AI methodologies can even personalize learning experiences further down the line. AI that recognizes emotion can analyze emotional states through video or voice inputs, allowing adaptive adjustments of learning pathways that align with the emotional and engagement states of the learner. Also, predictive analytics can assess industry trends and career trajectories to determine future skill needs of learners, thereby providing innovative learning modules before the need arises.

6.2 Multi-Modal Learning Integration

Adding teleprompters, cream boards and a few other formats will increase the system ability for multiple learning formats. Integrating immersive technologies (e.g., virtual reality [VR] and augmented reality [AR]) also offers students hands-on learning experiences, especially in classes that come with a practical aspect, such as engineering, healthcare, and art. Gamification enhancements such as adaptive difficulty levels, achievement systems, and multiplayer challenges also contribute to improving learner engagement and retention rates.

6.3 Global Accessibility

Developing the capacity of the system to support different ways of learning will make it more versatile. Introducing immersive technologies (e.g., virtual reality (VR) and

augmented reality (AR)) offers hands-on educational activities, especially in practical domains such as engineering, healthcare, and art. These organizations can improve learners possibly even further by providing gamification improvements such as adaptive difficulties, achievement systems, and multiplayer tasking.

6.4 Enhanced Mentor Tools

Empowering mentors and organizations with advanced tools will enhance learner success. For example, AI can be used to generate tailored intervention suggestions that empower mentors with actionable recommendations to spot struggling learners and take appropriate action. In addition, AI-powered group dynamics analysis can help understand how individuals are collaborating in groups and provide recommendations to improve collaborative learning experiences.

6.5 Longitudinal Skill Tracking

Another task is developing the system's ability to track, and promote, long-term retention of skills. Craft algorithms that analyze skills over time to expose dips in proficiency or persistence areas needing remediation. To help users maintain proficiency in little-used skills, retention strategies can recommend period refresher activities or tailored pathways for learning.

6.6 Ethical AI and Data Privacy

In scaling the system, the need for ethical AI practices and user privacy will be of utmost importance. As AI systems itself are being used in this domain, the focus should be on having them audited continuously such that they do not show bias towards any groups and biases should be corrected whenever traces of it is found. Using blockchain and similar technologies, Decentralized data storage could provide users with more control over their personal information, resulting in increased trust and compliance with privacy legislation.

6.7 Integration with Broader Ecosystems

To scale the further impact, the system can be connected to external tools and global initiatives. Whether operationalized through an LMS or through a bespoke content delivery solution, enterprise systems integration can ensure that learning pathways are tracked with organizational goals and professional development needs. You are not lifeline; Lability make break in words helping education.

7 Conclusion

Traditional learning requires slight modification of e assessement, e content particuarly on part of the Transform based on learner and for traditional learners, thus leading to its broad nature and it fall under Evidence based Approach of AI – based systems combines the advantages of student-centered educational design with Intelligence style of approaches, helping to alleviate the limitations of traditional e-learning systems,which tends to a more content-based,rather than a learner-centric style. We use the latest AI technologies to allow students to navigate their academic journey in a

more accurate and meaningful manner." This agile platform reconfigures its key features– personalize learning pathways, reactive evaluations, and instantaneous help– so that learners are able to continually acquire relevant skills in a fast-changing world.

This novel system sets itself apart from existing systems by introducing dynamic adaptability, creating an interactive and engaging learning experience. With mentor tools, community discussion boards and performance analytics, it helps individual learners but also empowers educators and institutions to deliver better outcomes. Instead of a linear, static process, the proposed system makes education an interactive, dynamic experience, fostering life-long learners that will be prepared to address future challenges.

To summarize, the results provide evidence for improved skill acquisition, retention, and engagement, addressing the limitations of static recommendation systems in current platforms. The initial implementation appears promising, but this paper also takes the opportunity to highlight potential future work associated with scaling the capabilities, scale, and ethical considerations of the system.

With the advancement of industries and technologies, the need for adaptable, personalized learning solutions will only increase. Today, we witnessed a revolutionary shift in education with the introduction of the AI-Enhanced Personalized Learning Support System, paving the way for scalable, accessible and effective educational solutions for learners around the globe. Through continued support and advancements, this system could emerge as a cornerstone of contemporary learning, clearing a path toward a future of truly customized, comprehensive and transformative education.

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