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Smart Personalised Learning System

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Abstract: ***A Personalised Learning Platform leverages data analytics, machine learning and adaptive technology to tailor educational content to each student's particular strengths, interests, and rates of learning. The traditional classroom setting typically uses a single teaching method that all students are expected to follow, which often does not account for the varying degrees of understanding, prior knowledge, and engagement among individual learners. The approach taken here is to use an intelligent system that continually monitors how a student interacts with the Learning Management System (LMS), tracks his or her academic performance as a function of time (i.e., using timeseries analysis), and relies on data mining algorithms to identify behaviour patterns and recommend appropriate educational resources, quizzes, and feedback during the learner's interaction with the LMS. The overarching functions of this system are to create personalised learner profiles, deliver content that matches each profile (i.e., adaptive content delivery), assess the learner on a continuous basis, and monitor his or her overall progress in real time. The system will have numerous features that support learners in a collaborative manner and allow them to be part of a community of learners by sharing common interests and collaborating with others on the Learning Management System. By employing these recommendation algorithms and analysing students past performance, the proposed intelligent system will ultimately improve student participation, retention of information learned at school and higher academic achievement. The proposed research will also provide an overview of the intelligent system's architecture, major components/operations, and the measurement metrics utilised for effectiveness measurement. Based on initial experimental results, personalised learning has increased learner satisfaction and understanding vs. the historical model; thus, providing evidence as to how intelligent personalisation can change the way digital education is delivered and create a better, more efficient and learner-focused education model.***

Keywords: Spam detection, email security, machine learning, deep learning, phishing, natural language processing, cybersecurity, transformer models

1. Introduction

Educational institutions have witnessed an increase in the use of technology to impart knowledge worldwide.

Implementations like Moodle, Coursera, and Khan Academy have allowed for greater flexibility and access to education, but the traditional method of using one curriculum (the same content, pace, and method of assessment for all) creates considerable problems for many learners, particularly when considering prior knowledge, learning rates, interests, and cognitive abilities.

Personalised learning uses technology as a solution to the above limitations by using data analytics, machine learning, and user behaviour analysis to create tailored educational experiences (the learning experience) for individual learners. Today's systems can continuously monitor interactions (usage) with content, evaluate performance, and determine strengths and weaknesses of each student. This information enables systems to provide learners with relevant resources/activities/assessments/feedback based on their individual needs. This type of personalised/ integrated approach supports both individualised/ self-paced learning as well as promoting active engagement and ongoing development.

A Personalised Learning Platform combines all of the above intelligent technology with the goal of providing a learner designed educational experience.

A. Motivation

While digital learning systems like Moodle, Coursera, and Khan Academy are widely used, most current systems deliver content in a uniform fashion, which does not account for the diversity of learner differences. Learners will possess a variety of pre-existing knowledge, rates of learning, interests, and problem-solving capabilities; however, they are often given the same learning content and assessment. This disparity can lead to decreased levels of interest and motivation in studying, decreases in retention of knowledge, and differences in academic performance. This research is motivated to develop an adaptive learning system that will adapt the delivery of learning content and feedback based on each student's unique profile, thereby providing a more effective, interesting, and supportive learning experience via the personalization of learning.

B. Contributions of This Research

The goal of this research paper is to propose and design a Personalized Learning Platform that combines analytics, machine learning technologies, and assessments of learner behavior to deliver an adaptive learning experience. The paper provides a description of the system architecture, methods for developing a profile of the learner, mechanisms for recommending learning content, and processes for assessing student progress throughout a personalized learning path. Additionally, the paper establishes metrics to assess the efficacy of personalization on student engagement and performance. Finally, through experimental analysis, the researchers provide evidence of how the proposed system is superior to the traditional uniform learning model and the practical advantages of a personalized approach to learning.

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2. Literature Review

Earlier e-learning systems and Learning Management Systems (LMS) were mainly focused on delivering information and managing courses rather than adapting to individual students. For example, Moodle allows instructors to upload content, administer assessments and manage grading; however, the path that students take through the education process is static for every student. Researchers have identified that this static approach limits student engagement and does not account for the fact that students have different levels of prior knowledge, learn at different speeds, and have different cognitive styles. The original research performed on adaptive learning was on fixed-logic-type systems where the flow of content is controlled through predetermined conditions, but these systems cannot be easily adapted to accommodate the large diversity of learners that exist.

As researchers began to apply data mining and machine learning techniques, they began developing methods to create adaptive learning experiences for each learner; for example, recommendation algorithms, learner profiles, and learner behaviour analysis for predicting what a learner needs to experience and recommend resources that will continue to develop their skills. The first studies using adaptive learning/educational methods used classification-type algorithms, clustering-type methods, and collaborative filtering methods to group learners with similar performance, preferences, and interests. Similarly, adaptive hypermedia systems and intelligent tutoring systems were able to provide real-time adaptation of materials based on dynamic changes in presentation style and difficulty level. The findings of these studies demonstrate that adaptive learning systems improve the overall levels of student engagement, completion of courses, and performance in comparison to traditional LMS systems.

a) Traditional One-Size-Fits-All Learning Systems Have Significant Limitations

Traditional Learning Management Systems provide all individuals with the same content, assessments, and pace regardless of prior experience or ability. As a result, there is a tendency for fast learners to disengage and slow learners to become frustrated. Research suggests that most traditional Learning Management Systems are created to manage content, not to adapt to the needs of learners; therefore, the effectiveness of knowledge transfer and individualised support are severely diminished by this traditional approach.

b) Changing Rule-Based to Adaptive Learning Approaches Over Time.

Early adaptive learning systems were created using fixed rules. For example, an early adaptive learning system would typically employ the following type of rule: ”If your score is less than 50 percentage, you will view the remedial content.” While this type of rule-based adaptive learning system was helpful for most students, it was also very rigid; therefore, it could not effectively accommodate all learners or adequately address complex learner behaviours. Studies indicate that they require adaptive learning systems that can provide intelligently adaptive systems capable of dynamically adapting the learning path of individual learners according to real-time learner performance data, rather than pre-defined learning conditions.

c) Using Performance Data to Build Learner Profiles Is Critical to Personalisation.

Learner profiling is one of the main focuses of most personalisation research. In personalisation, learner profiling refers to the collection of prior learner performance data (i.e., scores) along with learning style, learning speed, and interaction history to create a learner profile for an individual learner in an adaptive learning system. The learner profile would enable the adaptive learning system to identify each individual learner’s strengths, weaknesses, and learning styles, and utilise this information to support creating and recommending learning paths to each individual learner.

d) Recommendation Methods Are Used to Help Educators Identify Relevant Content for All Learners

Recommendation methods are widely used in the ecommerce sector and the media industry, and a similar approach can be found in education in order to provide recommendations to educators regarding appropriate learning resources for each learner.

e) Intelligent Tutoring Systems Are Implementing Individualised Instruction

Intelligent Tutoring Systems mimic how tutors give hints or guidance through step-by-step instructions when learners have difficulty understanding concepts. Studies show these types of systems support concept acquisition because they are able to help learners immediately when they need help.

f) Adaptive Tests: Real-Time Feedback, Provide Interactivity to Education

Adaptive tests provide different levels of difficulty based on the answers given by the learner. Real-time feedback allows learners to correct their mistakes immediately after making them and reinforces what they have learned, making learning more interactive and effective.

g) Learner Engagement Retention Are Impacted by Personalization

Researchers have shown that when learners experience individualized content based on their current level of knowledge and interests, they tend to have increased participation and motivation. Therefore; the rates of learners dropping out of school will decrease and their retention of knowledge will be enhanced when compared to learners using traditional educational systems.

3. Research Gaps and Problem Statement

The vast majority of existing digital learning platforms provide learners with exactly the same content and assessments; they are very limited in the way that they adapt based on a small number of predetermined rules. Little to no consideration is given to how learners behave, their history of performance, the types of resources they have interacted with or how they interact with resources. Previous studies have shown that there are many gaps in the way that digital learning platforms function; these gaps include a lack of real-time adaptive feedback, a weak learner profile system that fails to provide enough detail about individual learners, poor

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integration of learning analytics for the purpose of using machine learning, and learning paths that cannot be continuously updated as the learner progresses. The outcome of this is that learners with different learning speeds, interests, and levels of understanding all receive the same set of materials to study from. This has resulted in low levels of engagement, poor knowledge retention, and, therefore, inconsistent performance in the academic realm.

As a result of these issues, the problem that this research is addressing is the design of a smart Personalised Learning Platform that can collect and analyse learner data, form detailed and accurate learner profiles, and make dynamic recommendations for content, assessments, and feedback to each learner. This work will create an interactive and dynamic educational system that is built around using data analytics and machine learning algorithms to provide a continuous improvement of the instructional and overall effectiveness of digital learning platforms by building a system that addresses the limitations of traditional digital learning systems as well as improving the overall effectiveness of learning.

a) Standardized Content Delivery Fails to Account for Indi-vidual Learning Differences

Standardized content, instructional pace, and assessment are provided to all students through digital learning platforms regardless of previous knowledge, individual learning speeds, or personal interests. As a result, engagement and effectiveness will decrease if one group of students can quickly master concepts and become bored while other groups struggle to keep up with the instructional pace. This disconnect will continue to occur over time, leading to a high level of dissatisfaction with their progress and decreased motivation to engage in future learning activities. Therefore, research supports that supporting the individual learning pace of students will lead to improved learning and satisfaction. Consequently, standardized content delivery represents one of the greatest shortcomings of contemporary digital learning environments.

b) Limited Solutions to Adaptive Learning Require Basic Rule-Based Implementation

Older generation adaptive learning systems are based on fixed rules (such as low scores indicating that a student requires remediation), Fixed rules provide no flexibility and do not provide the necessary response to the more complex learning behaviours exhibited by the current generation of learners in real-time. Most fixed rules do not take into consideration the other significant factors that influence learning behaviours, such as how much time a student has spent on a particular topic, the number of times a student has made an error while working on a specific topic, and the students' preferences for learning various subject areas. Therefore, many students' learning behaviours are much more complex than fixed rules can adequately accommodate. Therefore, fixed rules will typically provide inaccurate or inapplicable study materials or assist a student in finding the best learning path or methodology

c) Limited Application of Learner Profile Data and Learning Behaviour Analytics

The majority of digital learning systems provide poor learner profiles based on existing performance, historical interaction and preferences data, resulting in limited individualisation for the learner. Consequently, if the learner's profile data is not accurately established and maintained, the digital learning system cannot support appropriate responses to individual learners and will reduce retention of course materials.

d) Research Problem Statement

An intelligent personalised learning system that can analyse student data in order to create a personalised experience for each student is needed. Other learning systems currently available today do not effectively analyse how students learn, how well they perform on tests, and what types of interaction they typically have with the learning materials; therefore, they offer a one-size-fits-all approach to students in regards to the materials and assessments that each student receives. As a result, there is less engagement and lower levels of student achievement because students are receiving the same materials and assessment even though they may have different abilities, interests, and levels of understanding. The proposed research will focus on creating accurate learner profiles and making recommendations to learners regarding the most appropriate content or quizzes and feedback based upon their performance at any given time. The system will combine learning analytics, machine learning, and adaptive assessments into a cohesive system that will continue to create evolving pathways of learning for the student, as well as provide the student with real time feedback that is personalized to their experience in order to improve knowledge retention, satisfaction with the learning process, and overall academic success.

e) Need for continuously updating and dynamic Learning Paths

Learning is an ever changing and dynamic process in which the learner changes both their understanding of the material and their ability to perform the task as they progress through the learning process. Fixed pathways, as provided by traditional learning systems, do not allow for change as the learner changes during the course of the learning process, resulting in learners being either bored or overwhelmed with materials at the time. Therefore, a personalized learning system must continuously measure how well the learner is progressing through the learning process.

f) The importance of recommendation systems to education

Recommendation systems were developed for e-commerce, but have been adopted by many educational platforms to provide recommendations on additional learning resources. Recommendations are typically made for videos, notes and quizzes based on user interests and previous usage. There are two types of filtering methods to generate recommendations: content-based filtering (finding items similar to your previous selections) and collaborative filtering (using the behaviors from similar users to generate recommendations). These recommendation systems save learners a great deal of time by helping them locate relevant study resources. Personalized recommendations have also been shown to increase student motivation, and therefore participation. Previous research has shown that recommendations can improve a student's ability to learn efficiently; it can also enhance a student's understanding of concepts by directing the learner's focus to

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relevant materials. Recommendation techniques will continue to play a key role in future personalized learning systems.
- Content-based vs. collaborative filtering
- Recommendations for relevant study resources
- Increased learner engagement
- Increased learner efficiency

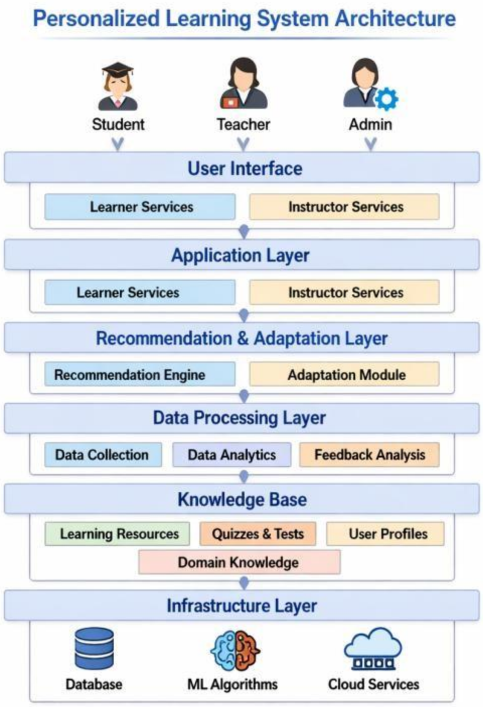
g) Machine Learning Use Cases with Personalized Learning

Machine Learning is a critical component of analyzing massive amounts of learner data. Using methods such as classification and clustering these algorithms will categorize learners based on patterns that are similar. ML can also predict the best learning pathways and what level of content should be introduced at any given time. Also, ML completely automates making personalization decisions without human input. Researchers have noted that implementing ML into a system will enhance the intelligence and adaptability of that system.

The way these algorithms are designed allows the machines to learn from data collected after each time an action is performed within the system. This increased learning and enhancement will allow machines to provide accurate and efficient personalization to each learner. As a result of the above reasons, ML is an integral part of contemporary personalized learning systems.
- Classification and Clustering
- Predicting appropriate learning pathways
- Automating Personalization Decisions
- Learning continuously from data

4. Architecture Model

The personalized learning platform contract has been designed as a hierarchical structure for effective adaptation to meet individual learner needs based on their activities. First, the learner's activity is captured and converted into structured data for analysis. This structured data is then utilized to build dynamic learner profiles that represent learner strengths, weaknesses and preferences. The next step is to use an intelligent recommendation engine to identify appropriate learning content and paths for the learner, with the added benefit of continually refining the personalization of the platform through a feedback loop.
- **Layer 1**- Learner Interaction: All raw data inputs will be collected by users (i.e., clicks, page views, quiz attempts, time spent on subject matter, navigation) within the learning environment through either web-based or mobilebased platforms.
- **Layer 2**- Data Processing and Feature Extraction: The raw interaction logs are transformed into structured representations of features (i.e., rate of learning, expressed interests in subject matter, accuracy rate, frequency of return visits, and level of activity engagement).
- **Layer 3**- Learner Profiling and Modeling: Utilize analytical techniques (and machine learning techniques) to create dynamic profiles of learners, which represent their strengths, weaknesses, areas of interest, and places where they have knowledge deficits.
- **Layer 4**- The Personalization and Recommendation Engine: Leverage the learner profile for the recommendation of individual learning materials (e.g., videos, quizzes), difficulty levels, and learning pathways suited specifically to each individual.
- **Layer 5**- Content Delivery and Adaptation: Access the appropriate videos, notes, and assessments from the content repository and adapt the sequence and difficulty based on the recommendation.
- **Layer 6**- Feedback Loop and Continuous Improvement: Continuously review the learner's performance and incorporate performance feedback into updating the learner profile to utilize when retraining the recommendation logic for the future.



5. Discussion

Personalized learning platforms signify a considerable change from standardised digital education systems to flexible learner-focused environments. Personalized platforms collect detailed interaction data about individual learners and analyse the data intelligently in order to gain an understanding of how each individual learns, where they encounter challenges and which topics need more focus. This enables the platform to deliver content in a more tailored manner rather than providing static content, thereby creating more personalised experiences for learners. Increased engagement from learners and decreased frustration associated with having the wrong level of content are the result of establishing personalised learning environments.

The layered structure that is proposed within this system is the key to achieving successful personalisation. Each of the five layers, from data collection through to feedback, helps to construct a complete picture of a learner. Raw interaction data is converted into a structured form and used to develop dynamic learner profiles. These profiles then drive the recommendation engine for content, quizzes and learning paths.

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This clear separation of responsibilities across the different layers enhances both the organisation of the overall system and facilitates better scalability.

Another key concept discussed is the potential for datadriven decision-making within the context of education. Rather than using fixed rules as the basis for delivering content, the platform continuously analyses learner activity in order to constantly improve the quality of recommendations. The result of this ongoing analysis means that the more a learner interacts with the platform, the better personalisation will occur. This ability to learn continuously from learner activity is also a key factor in the long-term success of the platform.

6. Limitations

The success of the Personalised Learning Platform relies on the quality and abundance of accurate learner interaction data; if there is insufficient or biased data available, this will negatively affect the performance of the system. A large amount of processing power is needed to train and run machine learning models, which can increase costs and complexity. The system faces significant challenges in making accurate recommendations to new users because of the cold start problem. Scalability can become a challenge as the number of learners using the platform at the same time increases and realtime processing is needed. The privacy and security of learner data remain a significant challenge.

1) Tagging Content Quality: Personalised learning relies on more than algorithms; it also relies on the quality and appropriateness of the learning material for the learner's needs and how well the learning material is tagged. If the learning content is not well-organised (e.g., using tags/labels) or the tags used are poorly labelled, inaccurate recommendations may occur irrespective of whether the learner model is accurate.
2) Risks of Over-personalisation: Over-personalisation could restrict a learner's learning to either a limited number of topics or only to types of the easiest materials, thus restricting their exposure to many other types of concepts. Consequently, over the longer term, this has the potential to impede a learner's overall development of critical thinking abilities as well as their overall ability to acquire a well-rounded education.
3) Variable Learner Motivation: The expectation is that all learners will engage with the personalised learning experience regularly. Factors such as level of learner motivation, overall learner well-being, and/or environmental factors can influence a learner's frequency and/or type of interaction, and would result in potential false positives or false negatives from the analysis of their behaviour.
4) Challenges of Integrating Traditional Teaching Methods: Personalized platforms may encounter difficulties in blending with traditional teaching methods or fixed academic curriculum structures where teachers have a pre-defined syllabus and timetable to follow
5) Real-time Delays in Adapting Learning Path: Even though the system plans to adapt learning paths dynamically, large amounts of data must be processed before giving recommendations to the learners, which could cause delays in content adapting.
6) Internet Reliance: The Learning platform functions online using cloud-based computing, meaning poor or unstable internet connections will inhibit learner access and impede system performance.
7) Challenges in Evaluating Academic/Achievement: To get a precise picture of how much personalising has benefited students' acquisition of knowledge/skills will be difficult because long periods will be needed to evaluate/monitor out-of-system analytics.

7. Future Research Directions

An arm of personalisation in learning will be a better recommendation system that is more accurate and smarter, using state-of-the-art deep learning and hybrid AI algorithms. Another area is how the integration of reinforcement learning can be used to create more dynamic personalised learning paths and adjust them in real-time based on each learner's performance. In addition, research can be conducted on how to develop better explainability algorithms so learners and educators can understand why a particular piece of content has been recommended to them.

1) Integration of advanced AI models: Future studies on hybrid deep learning, reinforcement learning, and advanced recommendation systems- including their application to personalised learning- could improve the ability of the personalised learning systems to predict individual learner behaviours and create an accurate learning path for each learner.
2) Transparency of AI models used in educational systems: Research could include ways to increase the learners' and educators' understanding of the logic behind the recommendations and the learning paths provided to improve trust and usability.
3) Improvement of real-time adaptive learning: Future studies could provide an improved understanding of how to process learner data in real-time so that learners receive immediate changes in learning content and sequence based on their ability to perform and interact.
4) Development of Privacy Preserving Learning Systems (PPLS): The focus could continue to encourage use of secure data handling practices (e.g., federated learning, encryption, etc.) that could keep secure learner data while also allowing sufficient information to make the learner experience easy to personalise.

8. Conclusion

This research proposes a Personalised Learning Platform that effectively changes how digital learning has traditionally been delivered, moving from an instructor-driven perspective (instructors controlling what students experience) to one that is learner-centric (students having control over their own experience).

Unlike traditional Learning Management Systems (LMS), which deliver learning content, assessments, and learning paths in a one-size-fits-all fashion, this Personalised Learning Platform adjusts content to the needs of the individual. The platform uses learner behaviour, performance, and interaction pattern analysis to personalise content by providing more meaning and relevance.

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Machine Learning, Learning Analytics, and Recommender Systems are instrumental in achieving personalisation. These technologies create accurate learner profiles through the collection of repeated measures of learner behaviour, performance, and engagement. They also predict suitable learning paths based on individualised profiles. Personalisation through this type of feedback mechanism continues to improve over time, resulting in a highly adaptive Personalised Learning Platform. The research conducted shows clear evidence that Personalised Learning is significantly more effective than traditional methods in terms of improving learner engagement, motivation, and knowledge retention. By providing learners with content based on their capability and interest rather than using a prescribed path to deliver content, the learner will be less frustrated and have an improved overall learning experience. Additionally, Personalised Learning allows for selfpaced learning and provides the learner with the opportunity to determine how they learn best.

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