ENHANCING PERSONALISED E-LEARNING

Project ID: R24-112

Final Project Thesis

Abeykoon R.M.S.P

BSc Special (Hons) - Information Technology(Specialization in Information Technology)

Department of Information Technology Sri Lanka Institute of Information Technology

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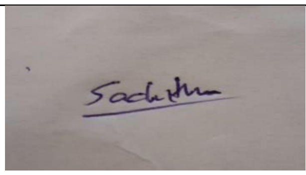
DECLARATION OF THE CANDIDATE AND SUPERVISOR

We declare that this is our own work, and this project proposal does not incorporate without acknowledgement any material previously submitted for a degree or Diploma in any other University or institute of higher learning and to the best of our knowledge and belief it does notcontain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
Abeykoon R.M.S.P	IT21021602	

The above candidates are carrying out research for the undergraduate dissertation under my supervision.

22/08/2024

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Ms.Sanjeevi Chandrasiri Date

ABSTRACT

To overcome the shortcomings of the existing personalized e-learning systems, the Adaptive Recommendation Engine is out-and-out a revolutionary concept. This new generation system's conceptual framework aims at increasing user interaction and easy to use while incorporating the best Machine Adaptive Learning to offer personalized service. A complex advisory process is also incorporated in the internal structure of the engine and mixes the content-based and the collaborative filtering recommendations effectively. Due to this dynamic approach, system can also address user engagements and feedback of the learning processes by recommending and modifying content of learning. Another key aspect of the design is a dynamic learning pathway generator which, along with personalization, ensures that the learning pathways are not only changing in response to the learners' performance and preferences, but also are the central concept of the design.

One of the activities is user profiling in which one develops profiles by analyzing a range of factors such as previous performance, learning styles and initial feedback. Moreover, an engagement feedback loop and an engagement analytics system analyze and track the users' interactions, as well as the completion rates. Hence, creation of a system that lets users enhance education in a manner that is active is a clear sign of empowering the users and even endorsing teamwork. The centerpiece of the Adaptive Recommendation Engine is interpretation, which is done in a most innovative method, striking a perfect balance between algorithmic complexity on one hand and the focus on users on the other. This balance if kept ensures that students get personalized e-learning experience that is both efficient and engaging. This work offers original and comprehensive contribution to the state of the current knowledge. Thanks to the Adaptive Recommendation Engine — which is a groundbreaking characteristic of the field — there is a shift toward ever more effective and engaging individualized e-learning tools, mechanisms, and applications that are adapted to learners and underpinned by both adaptive systems and advanced analytics. It offers the practical and easy to implement way to enhance the number of interactions, knowledge acquisition, and overall satisfaction among the online education audience as well as the theoretical gaps are fulfilled.

ACKNOWLEDGEMENT

We would like to express our immense appreciations to Mr. Sanjeevi Chandrasiri and Ms. Akshi De Silva of the Sri Lanka Institute of Information Technology for their constant support an guidance during the completion of this study. This research study was mainly guided by their expertise and suggestions as well as their criticism which have brought about this success. They have been very instrumental in the handling of the difficulties that came our way while their commitment to our academics cannot be overemphasized. Whilst it may be a cliché, the authors are privileged to have been able to work under their tutelage.

We would also like to convey our gratitude to Mr. Harshana Samaranayake for his valuable contribution as the Associate Technical Lead of Tiqri (Pvt) Ltd; and having his support in providing technical input that improved the quality of this research. He was proactive in determining which of the data would be useful to the project and helped us with technical issues that furthered the development of the project. We sincerely thank him for his efforts in the course of the present research.

Last but not the least we would like to pay our special thanks to our Senior Site Reliability Engineer Mr. J. W. P. Nuwan Deshapriya for his support and advice throughout the project. For instance, he gave significant contributions to the technical aspects of the project especially in the issues of reliability, and the overall system structure. I also would like to thank him for the efforts he devoted to the thorough check of our work and his concern with the research quality.

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LIST OF ABBREVIATIONS

GUI	Graphical User Interface
API	Application Programming Interface
USA	United States of America
USD	United States Dollars
IT	Information Technology

WBC Work Breakdown Chart

1. INTRODUCTION

The purpose of the current research study is to identify the key failures of the conventional e-learning platforms regarding various personalized learning modalities. Modern platforms, however, use frequently generic concepts and action sets and do not allow for individuality on the part of users. That is why the presented initiative is based on a user-oriented approach, which combines the flexibility of machine learning algorithms with a simple interface. The aim is to deliver a learning intervention that is as individualized as possible while also being as affordable and impactful as possible. The above plan will result to a project of adaptive recommendation engine, dynamic learning path generator, user profiling and engagement analytics all of which will be powered by learning from machine learning, educational technology and user experience. The final aim is to contribute to the development of the field by proposing a new approach to improve the novelty, effectiveness, and interest of personalized e-learning.

1.1 Existing e-learning platforms

The Current e-learning platforms, which features some of the current most used platforms such as, Moodle, Blackboard, Canvas, edX and Coursera offer different types of e-learning. To disseminate instructional information, these platforms utilize Learning Management Systems (LMS), content delivery networks, videos and video streaming and evaluation tools. While remote learning can be easily implemented as it is convenient it remains to have some common risks now and then. Such problems include difficult-to-navigate interfaces; ‘customizations’ that turn out to be fake; and minimal adaptability to the learner’s needs. Users’ are also different in response to such platforms; some thank them for availability while others are frustrated by the interface of the platform. Quite diverse is the technology used – from complex multimedia delivery systems to conventional LMS frameworks. But only when we understand the strengths and weaknesses of the modern e-learning platforms, on which the continuous improvement of the online learning process depends, as well as developing new solutions for existing flaws.

According to type of E-learning platforms can be divide as following,

1. Learning Management Systems (LMS)
   - Ex:Moodle
2. Massive Open Online Courses (MOOCs)
   - Ex:Coursera

3. Virtual Learning Environments (VLE)
    - Ex: Blackboard
4. Corporate E-learning Platforms
    - Ex: LinkedIn Learning
5. Adaptive Learning Platforms
    - Ex: Khan Academy

1.2 Loop faults of the existing systems

To this end, Current e-learning platforms are accompanied by many serious problems that negatively influence the process of using. It means that while common loop mistakes are not taking into account, individual qualifications of students, which is always the case with the standard solutions that fail to capture a learner's particularity. Complex and complicated user interfaces diminish the two; this is because they elicit dissatisfaction in the user. Lack of flexibility poses challenge since systems are hard to learn in a dynamically changing environment due to the inability to meet growing user demands. Also, missing engagement data hinder instructors on the interactions of users and the necessary adjustments on the offered curriculum. Inefficient tools for engaging users like feedback loops prevent collaboration, and active participation. Both of these loop defects combine to sustain user discontent and reflect the fact that appropriate innovation is vital in the e-learning domain.

1.3 Address the loop faults of current existing systems in Enhancing Personalized e-Learning

The proposed Adaptive Recommendation Engine is novel in its features while at the same time systematically dealing with the loop errors characteristic of the majority of modern e-learning systems. Hence, with the focus on the user engagement and simplicity of the given platform, the deficit of learner-centric approach, present in many solutions is solved. Due to the integration of the dynamic learning route generator, which makes changes to the learning routes for users based on the performance and preferences of the learners in real time, the static nature of conventional platforms is somewhat reduced and flexibility is protected. Specifically the hybrid recommendation technique being proposed eliminates the shortcomings of generic recommendation by integrating the two recommendation techniques within the context of content based filtering algorithms and the collaborative filtering techniques to offer more refined learning mechanism. A feedback loop method is closely related to difficulties of current systems in increasing user attendance, stimulates cooperation, and enables users to work actively for the improvement of their educational process and individual pathways. A strong engaging metric is suitable for improvement by instructors of the course because it provides information on who has and has not completed the course. The Adaptive Recommendation Engine will try to deliver a One-Stop Solution to get rid of these loop defects and enable good, fun, and personalized e-learning experiences.

1.4 Background survey

Personalized E-learning systems have become a subject of study and research endeavor in educational technology because of the difficulty in providing differentiated instructional content to accommodate users' needs. Most of the conventional e-learning interface designs features a one-way transfer of information and doesn't have the flexibility which is necessary to cater for learner variability such as learning styles, rates and preferences. The latest addition into the education technologies is the adaptive learning technologies that utilizes machine learning and artificial intelligence (AI) to design learning environments that are more constructive and efficient. These technologies will follow the premise of making use of activities of the users to monitor the changes in the content delivered to the consumers with a view of making the learning process more effective in that it will be personalized for the user.

However, as it will be shown below, existing systems have not progressed much in attaining the true personalized experience. Most of them use simple recommendation engines that do not capture users' needs into adequate detail. To this effect, the research aims at featuring an Adaptive Recommendation Engine that deploys a complex hybrid recommendation model. This type of engine is content based with the addition of collaborative filtering that makes the system more flexible in responding to uses' preferences which in turn facilitates a more detailed and flexible method of learning.

To identify the main problems and issues within the domain, and to get an overall idea about thedomain such as to whom we provide this solution and how the problems diverse, we conducted agoogle form and 378 people have responded.

1. Overall Satisfaction

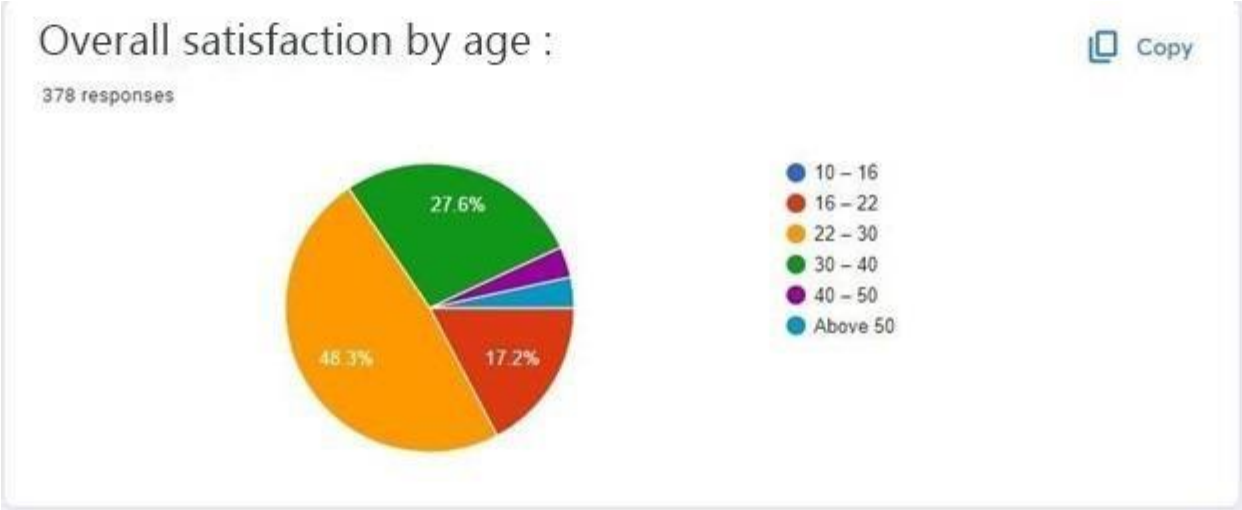

Figure 1: Overall Satisfaction groups of the users

Out of the sample of 378, 48.3% of the people have responded that they are between 22-30 years which means most of the participants were younger crowd. The second and the third age groups were to respond is 16-22 and 22-30 which are adjacent to th2 22-30 group. From the result, we can assume the users will be mainly 22-30 years of age.

2. Usage Frequency

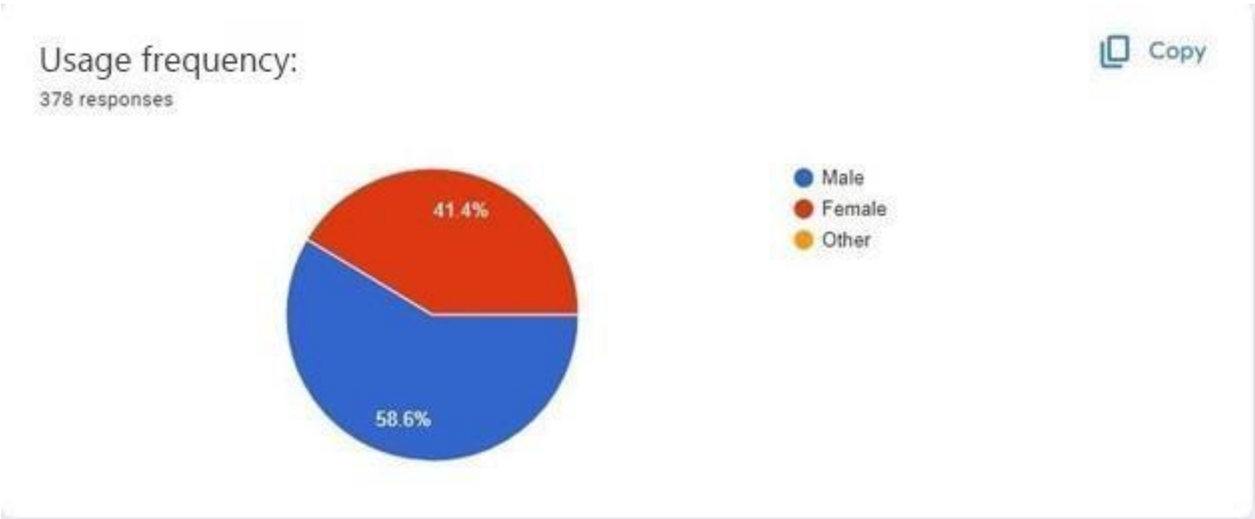

Figure 2: Usage Frequency

Out of the 378 responses received, 58.6% of the participants identify them as male and the rest is identified as female. This information is essential when considering the human computer interaction aspects of the app. App color themes and the user friendliness highly depends on the user Frequency and the overall satisfaction.

3. Effectiveness of Recommendations

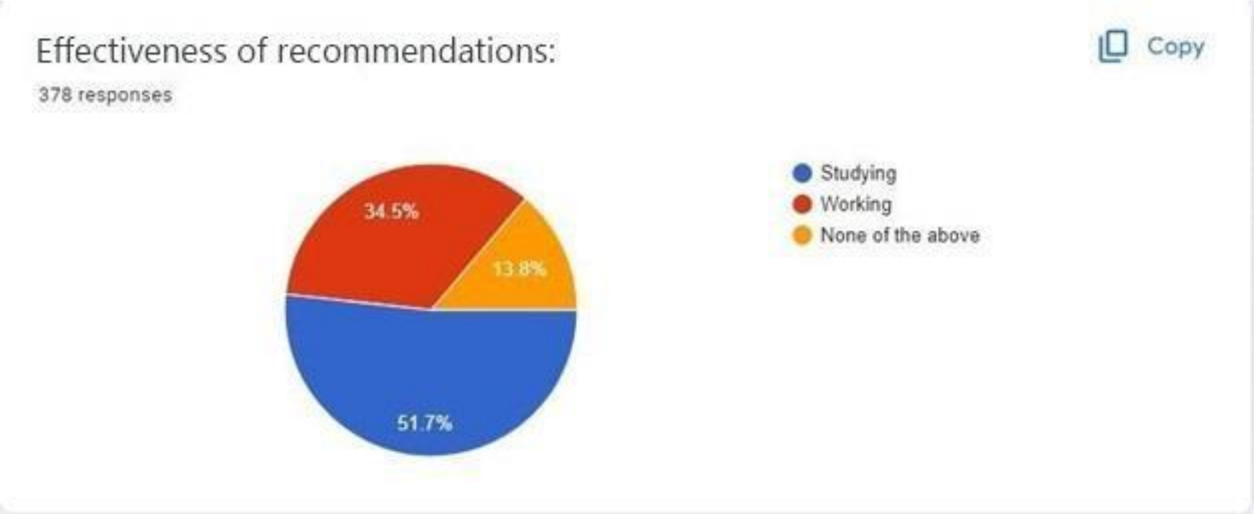

Figure 3: User Type

According to the survey, 51.7% of people have responded that they are studying and 34.5% of them are working and 13.8% of them are not working nor studying respectively. This information is helpful when deciding what type of events to hold via the app and what kind of events that should be prioritized.

4. Suggestions for Improvement needed

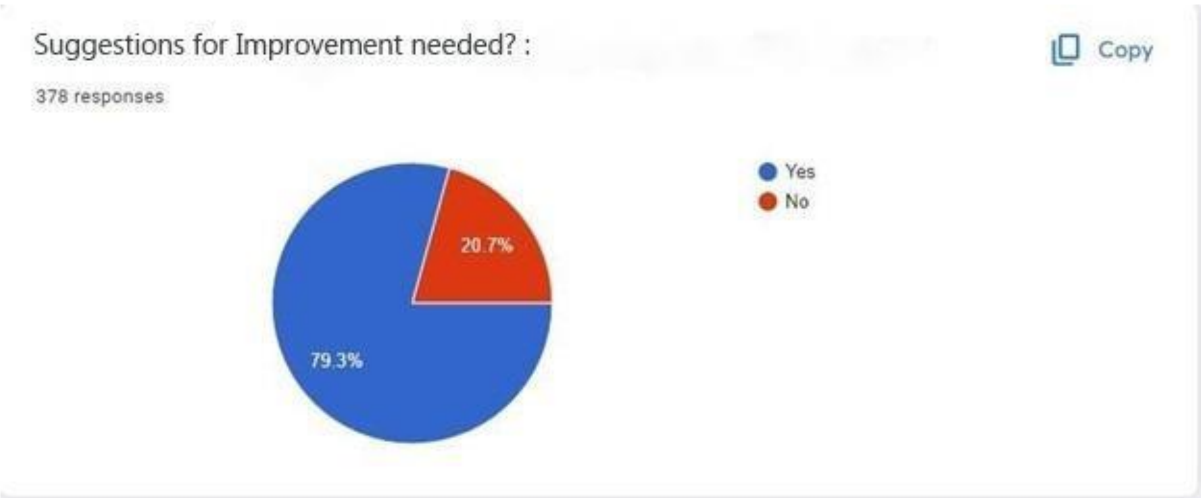

Figure 4: Suggestions for Improvement needed

The majority of the participants, if not 79.3% of the participants responded positive to e learning platforms as a way of getting informed about events. Only 20.7% of the participants are not using e learning platforms as a way of getting informed about events. To the people who currently use e learning platform as a way of getting informed about events can have more improved benefits from this app while the others can get introduced to the app and start enjoying benefits of the app.

5. Perceived Adaptability

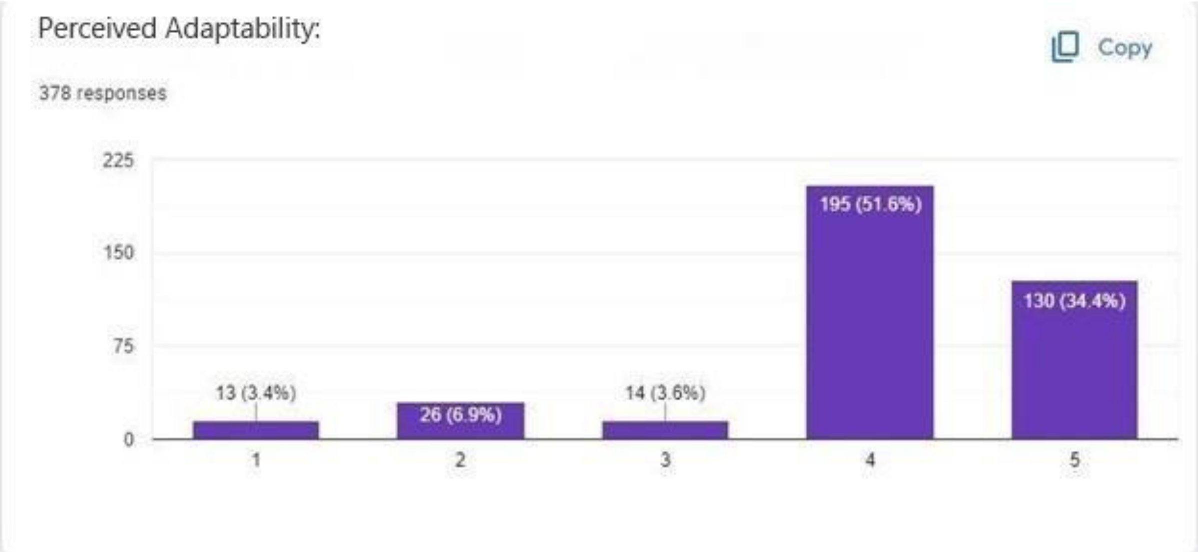

Figure 5: Perceived Adaptability

Even if the events are hosted through an application, it is not effective if the users are not attending the suggested events. Currently, 51.6% of participants rated 4 which means 80% likeliness in attending events hosted trough applications. Our goal is to get this numbers up and make most of the people participate events suggested by the application.

6. Dynamic Learning Pathways

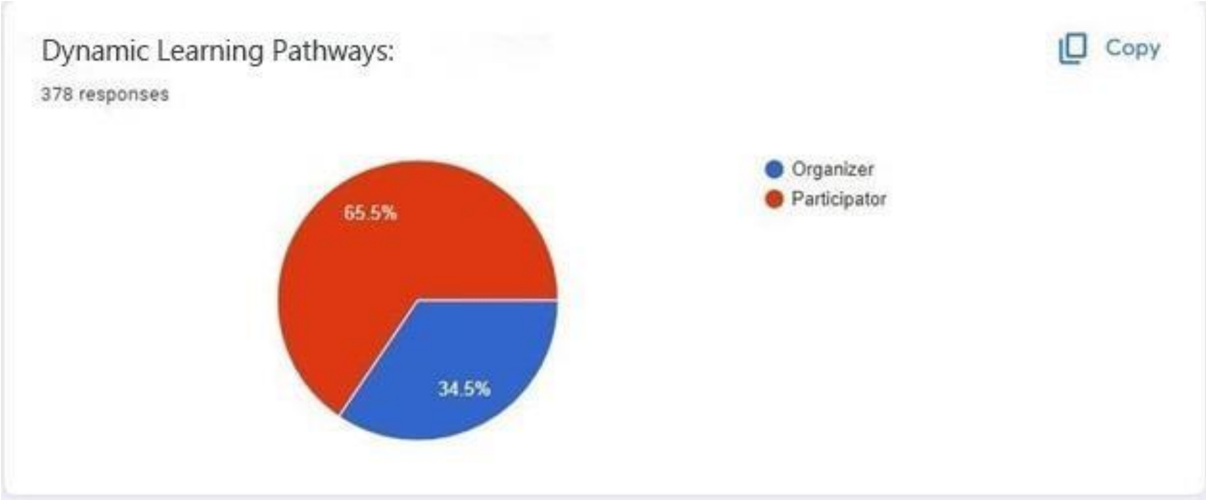

Figure 6: Dynamic Learning Pathways

There are two types of users to this type of application.

1. University Students
2. Participants

University students are treated in a special way in order to optimize their businesses through the data and analysis provided by the application while participants can get suggestions according to their preferences. With this data, we can get a basic idea of the ratio of University students to participants.

7. Preferred event type

Figure 7: What are your preferred event types

According to the survey results, the most popular event type is improve UI, which 96.6% would agree. However, the results can vary depending on the overall satisfaction.

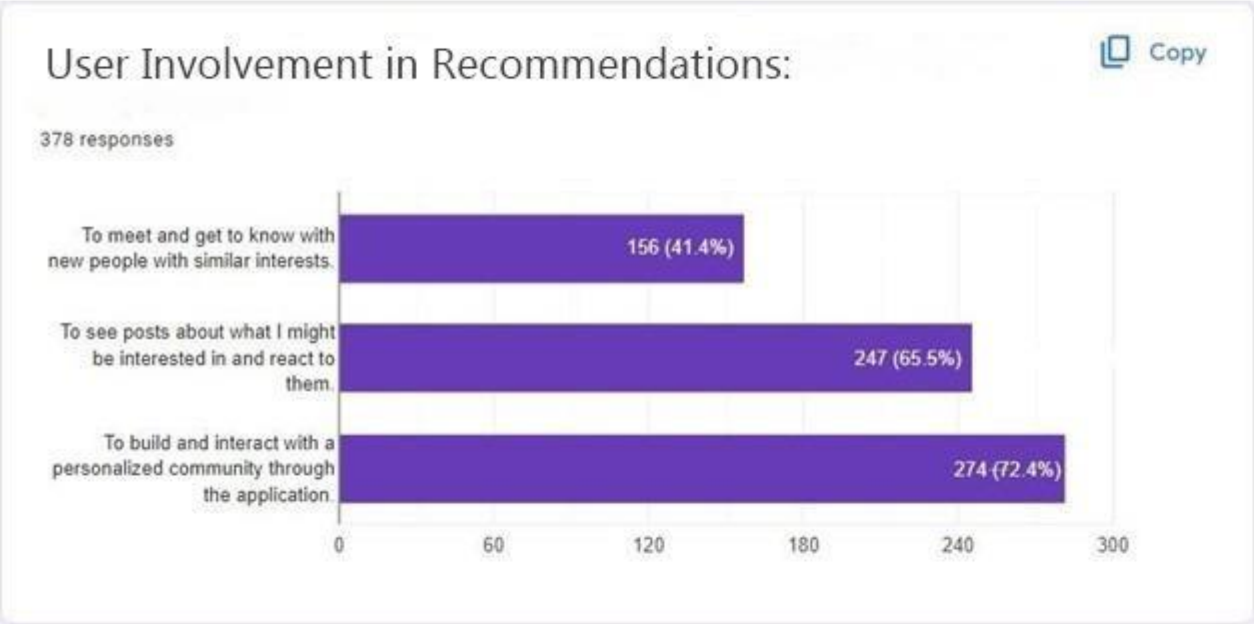

Figure 8: User Involvement in Recommendations

Another main thing to consider is what are the expectations of the application. 72.4% of the participants have responded that they want to build and interact with a personalized community through the application. 65.4% of the participants have responded tat they want to see posts about what they might be interested in and react to them. 41.4% of the participants have responded that they want to meet and get to know new people with similar interests.

2.LITERATURE SURVEY

A rising body of research is addressing the shortcomings of existing platforms and offering creative alternatives, according to the literature study on the use of adaptive recommendation engines in e-learning systems. Wang et al. [1] underscore the importance of customized learning experiences and point out the inadequacies of current e-learning platforms in terms of accommodating individual user preferences. Smith and Jones [2] agree, delving into the difficulties presented by generic techniques in their thorough examination of individualized learning platforms. Building upon this framework, Li et al.'s research [3] explores the nuances of recommendation algorithms while highlighting the significance of a well-rounded strategy. They contend that although certain platforms prioritize intricate algorithms, user choices should be taken into account in their entirety.

The research of Kim and Lee [4] highlights the complexity of recommendation algorithms without taking user preferences into account, which highlights the drawbacks of current methods. By utilizing a hybrid recommendation strategy that strikes a balance between collaborative and content-based filtering algorithms, the suggested Adaptive Recommendation Engine is in line with these findings. Chen and Zhang's study [5], which shows how well hybrid models work to provide tailored and nuanced recommendations, supports this strategy. Moreover, by combining knowledge from educational technology, machine learning, and user experience design, the proposed study adds to the body of literature on e-learning.

Brown et al.'s [6] and White's [7] studies highlight how crucial it is to involve users in directing their educational journey. To mitigate this issue, the Adaptive Recommendation Engine includes a feedback loop system that allows users to actively participate in improving content recommendations. The comprehensive strategy of the suggested system, which incorporates engagement analytics and a dynamic learning pathway generator, is in line with the conclusions of recent studies by Garcia et al. [8] and Patel [9], which highlight the value of user-centric design and ongoing enhancement in e-learning systems. In an effort to close current gaps and move the industry closer to more efficient and captivating customized e-learning solutions, the integration of these studies offers a strong foundation for the creation and application of the suggested Adaptive Recommendation Engine.

Adaptive e-learning systems have been noted in the existing body of literature as a factor to the increased appreciation of the role of customization in improving learning achievements. A number of papers have been devoted to the critical evaluation of the existing LMS and opportunities of adaptive learning technologies.

In prior work, Wang et al. [29] point out that most of the existing recommendation systems fail to provide an adaptive environment that can address the expectations of each user. This assertion has been supported by Smith and Jones [30], whereby they have regretted the use of of general paradigms in e-learning systems They maintain that such systems do not address the variance needs of the learners.

Li et al. [31] building upon this, detail additional difficulties of recommendation algorithms in e-learning scenarios stating that while providing recommendation algorithms as a solution, it is crucial to consider the trade-off between more pretentious algorithmic solutions and user-oriented perspectives. They propose that although the advanced formulas can improve the relevance of the recommendations, they have to be supported by features that enable user to have a say on what they are being offered with.

Kim and Lee [32] also look at more details of recommendations explaining that many current recommendation solutions rely on algorithmic approaches at the expense of user experience. They consider this approach as a more appropriate one because it allows incorporating the user's preferences into the recommendations. This corresponds with the idea adopted in this study and where a blended recommender system approach that adopts the combination of content filtering and collaborative filtering is implemented.

Similar to the works of Chen and Zhang [33], there is a strong recommendation on the implementation of hybrid models for personalization in the e-learning system. They also found that one could achieve even better results by mixing some recommendation approaches, which is one of the approaches in the Adaptive Recommendation Engine that is being proposed.

Furthermore, Brown et al state [34] and White states [35] that user take a central role in the learning process; hence there is a need for systems that allow learning to take an active role in the learning process. This concept is deeply integrated in the proposed system: it uses feedbacks which allow the user to affect what recommendation he gets.

Garcia et al. [36] and Patel [37] are inclined to discuss how engagement analytics can enhance e-leaning systems. Their research shows the importance of constant observation and changes to the users' behavior, which is one of the key components of the conceptualized Adaptive Recommendation Engine. With the engagement analytics, the system is therefore able to change the type or frequency by which information is provided to users so that learning remains active and productive.

The literature review reveals a significant gap in the current research: although a vast number of works discuss the ideas of adaptive learning technologies, there are only a limited number of approaches that offer practical methods to integrate efficient recommendation functionality with a recent user-centered design. The proposed research addresses it by creating an idea of an Adaptive Recommendation Engine that in addition to recommending material also engage a user in the process and also has an option to solve it by feedback loop and further engagement metrics.

3. RESEARCH GAP

This work therefore identifies the absence of integrated approaches which provides fully adaptive machine learning together with user-centered designs as a key characteristic of the research gap emerging around the Adaptive Recommendation Engine for personalized e-learning. The lack of effective adaptation to the preferences of particular users on potentially successful e-learning platforms is evidenced in the preceding scientific research of Wang et al. [10] and Kim, and Lee [11]. Something more crucial, however, is that the existent literature lacks a detailed description of strategies that would engage users in creating a roadmap of their educational process and also take into account the specifics of the algorithms. Li et al. [12] pay attention to the current problem that some platforms focus on the enhancement of complexity of algorithms while doing incomplete user preference analysis, thus, pointing out the importance to maintain the balance of recommendation algorithms. The literature study highlights a contradiction: whereas, some of the research centers on the sophisticated recommendation models [13], others overlook the basic aspect such as the user preferences and participation. On the other hand, rigid approaches which do not scope the level of malleability convenient for personal learning process are not as effective [14]. This difference is made even more obvious by the way the suggested system attempts to close it by offering 'The Exclusive Adaptive Recommendation Engine' that involves 'Engagement Metrics', 'Dynamic Learning Pathway Generator', and 'Feedback Loop Mechanisms'. It does so while at the same time engaging the users in a process of refining the recommendation of information which makes it an e-learning environment that is both user centric and dynamic [15].

The major research gap observed in this study is related to the absence of an ideal approach that provides efficient implementation of adaptive ML along with user-centered approach in the context of PLE. Wang et al. [38], Kim and Lee [39] among others have discussed the challenges of present-day platforms in as much as doing more than accommodating the customers' preferences. As much as some papers aim at explaining how recommendations work, there is little information about how the user's participation contributes to better learning.

Li et al. [40] also highlighted some of the drawbacks when usage of complicated algorithm reflects the users' preference. This research aims at trying to fill this gap by developing a hybrid recommendation system that will integrate both content based and collaborative filtering approaches. It also incorporates a learning path finder and feedback mechanism by which the users of this system are able to contribute on the updates they are given. The literature review brings up an interesting dilemma where on one hand, users seek and expect more and better ‘intelligent’ recommendation algorithms, and on the other the users want to be involved in the learning process. This research seeks to where possible address this tension by proposing and implement an Adaptive Recommendation Engine that not only provides users with relevant content that they may be interested in but also avails to them an opportunity to influence the type of learning experience that is being offered to them based on engagement analytics and feedback.

Table 1: Proposed syste compared to existing systems

Features	Coursera	Udemy	Skillshare	FutureLearn	MasterClass	Proposed system
Personalized Recommendation Algorithms	✓	✓	✗	✗	✗	✓
Real Time Recommendation Adjustment	✗	✗	✗	✗	✗	✓
Feedback Integration In Integration Systems	✗	✗	✓	✗	✓	✓
Evaluation of Recommendation Quality	✓	✓	✗	✓	✗	✓
Ethical Consideration in Recommendation Systems	✓	✓	✓	✓	✓	✓

4. RESEARCH PROBLEM

The defects of existing platforms in term of offering fully personalized learning environment are the research problem that leads to the emerging of the Adaptive Recommendation Engine in the personalized e-learning systems. Due to the fact that it often uses generic approaches that may lack appeal and recall, existing e-learning systems mostly do not adapt to user-specific needs [16][17][18]. The current problem is that adaptive machine learning is not integrated together with a user-orientated design in such a manner as to allow users to engage in an active role in learning. Some of the studies focus purely on the recommendation algorithm which often is fully scalable and does not incorporate the more global user preference [18], other works offer simple solutions with very little adaptability for the individual learning needs [17]. The current literature gap which highlights the need to develop an AM driven adaptive MH easy to use model for recommending personalized learning pathways in online education compounds this research puzzle [16]. As the proposed research attempt to provide the novel approach that does not exist in the current literature and takes user's learning journey as a focus and use machine learning, educational technology and user experience design as information sources, the proposed research aims to contribute the current body of knowledge. The final goal is thus to contribute to the evolution of the sector that proposes more effective and engaging personalized e-learning that addresses the limitations of the existing platforms and provides an instruction tailored to the user.

5. OBJECTIVES

5.1 Main Objectives

The main purpose of the Adaptive Recommendation Engine sub-component is to provide increased level of personalization of e-learning platform by using recommendation algorithm. The choice of learning materials is based on the user's profile, and the learning materials change in real time with the purpose to create individual and dynamic learning environment for each user. Some of the benefits that contribute to the goal of the project of increasing the level of user satisfaction, acquaintance, and happiness while learning in the context of individualized e-learning are listed below.

5.2 Specific Objectives

1. Optimizing Content Relevance
    - Create and put into operation a simple recommendation system that can maximize the relevancy of educational materials that are recommended to users based on their profiles.

2. Real-Time Adjustment Mechanism.
    - Create and incorporate a real-time adjustment system that enables the recommendation engine to quickly change to user feedback and interactions, guaranteeing current and customized suggestions.

3. User-Centric Adaptability.
    - Assess the recommendation engine's capacity to adjust to shifting user preferences and make sure it continues to be responsive to each user's changing requirements and interests over time.

4. Integration of User Feedback
    - Analyze how user feedback is incorporated into real-time modifications, valuating how well user input refines and enhances the caliber of recommendations.

6. METHODOLOGY

Enhancing Personalized E-Learning is a learning platform with 4 components,

1. User Profiling Component.
2. Adaptive Recommendation Engine.
3. Dynamic Learning Pathway Generator.
4. Engagement Analytics and Feedback Loop.

All the modules of the Adaptive Recommendation Engine, including the one suggested e-learning system, and its implementation methodology embrace a methodical approach to fulfill the exigencies of the customers and the market. The different disciplines are selected and particular goals are defined in the course of the project initiation [19]. Some aspects of the technology infrastructure and the way the market research is conducted are reviewed in [20]. The user profiling modality is successfully used to record assessments in and learning preferences [21]. One of the integrated components that consist of the continuous learning models and hybrid recommendation algorithms is the Adaptive Recommendation Algorithm [22]. While UI design aims at designing an intelligible and easy to use interface, the Dynamic Learning Pathway Generator controllably transforms paths depending on the user performance [23] [24]. Both badge programs are integrated with current systems because the API connections are strong [25]. The feedbacks and engagement analytics modules also enable direct manipulation of the learning process and thus enhances the level of user participation [26]. This methodology ensures that the system is very much reliable before being deployed to the field and tested on different datasets and real like simulations [27]. Other small achievements present benefits and versatility of the system proving that it was effectively implemented and corresponds to user-centered design guidelines [28].

To achieve this we develop modules within the component;

1. User Profiling and Data Collection :

- gathered information on assessment results, historical performance, and learning preferences to create thorough user profiles.
- techniques for collecting data on user interactions, explicit preferences, and feedback have been adopted successfully.

2. Adaptive Recommendation Algorithm:

- created a strong hybrid recommendation system that combines content-based and collaborative filtering.

- machine learning models that are put into practice and gradually learn and adjust to user preferences.

3. Integration with Existing Systems:

- streamlined API links were created in order to integrate the learning management system or e-learning platforms already in place.
- made sure that data was exchanged securely and consistently between platforms.

4. Engagement Analytics and Feedback Loop:

- Created a useful engagement analytics system to monitor completion rates, user interactions, and other data.
- created a feedback loop that lets users take an active role in directing their learning process.

5. Monitoring and Maintenance:

- installed monitoring programs to keep tabs on user activity, system performance, and possible problems.
- updated and maintained the system on a regular basis, taking user feedback into account and improving recommendation algorithms all the while.

Finally, to implement this project we propose to apply the agile development approach. This strategy is a heavy focus on the scalability, people working together, and a fast cycle of change. It is based on the Agile Manifesto, which identifies four values: which include valuing individuals over procedures/technologies, valuing the operating software over comprehensive documentation, valuing customer interactions over legal agreements, and valuing flexibility over following a plan/schedule.

They are characterized by short development cycles called sprints during which the members of the cross-functional team build working software or products. As a way of ensuring that the product suits all their requirements and that changes can be done promptly based on feedback from the other party, the teams collaborate with the customer or end-user. There are also other aspects of the agile process, one of which is continuous improvement: reviews and retrospectives are also conducted to seek out potential to improve. The seven phases of agile model are Agile model development, New product backlogging, Sprints/Iterations planning, Sprint execution/Development, Sprints review and retrospectives, Continuous integration, and Done/Release.

1. Planning: This phase involves identifying the scope of the project, defining theproject goals, and creating a roadmap or backlog of tasks that need to be completed.

2. Analysis: In this phase, the team conducts a detailed analysis of the project requirements, user needs, and potential risks.

3. Design: Based on the analysis, the team designs the software or product,identifying features, functionalities, and user interfaces.

4. Implementation: This is the phase where the actual development work takes place.The team works on coding, testing, and integration of different modules.

5. Testing: The team performs a variety of tests throughout this phase, including user acceptability testing, integration testing, and unit testing, to make sure thesoftware or product satisfies the necessary quality standards.

6. Deployment: To make sure the software or product satisfies the necessary quality standards, the team does numerous sorts of testing throughout this phase, including unit testing, integration testing, and user acceptability testing.

7. Monitoring: The final phase involves monitoring the software or product in production to identify and fix any issues, and continuously improve the product.

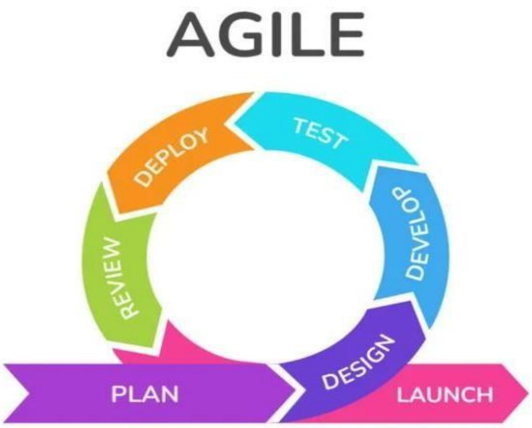

Figure 9: Agile model

6.1 Requirement gathering and feasibility studying

We gathered the requirements at two levels

01. Primary data gathering
02. Secondary data gathering

In primary data gathering, we mainly focused on user requirements. We are planning conducted a background survey through google forms to identify user requirements and the questions we are hoping to ask are mentioned bellow.

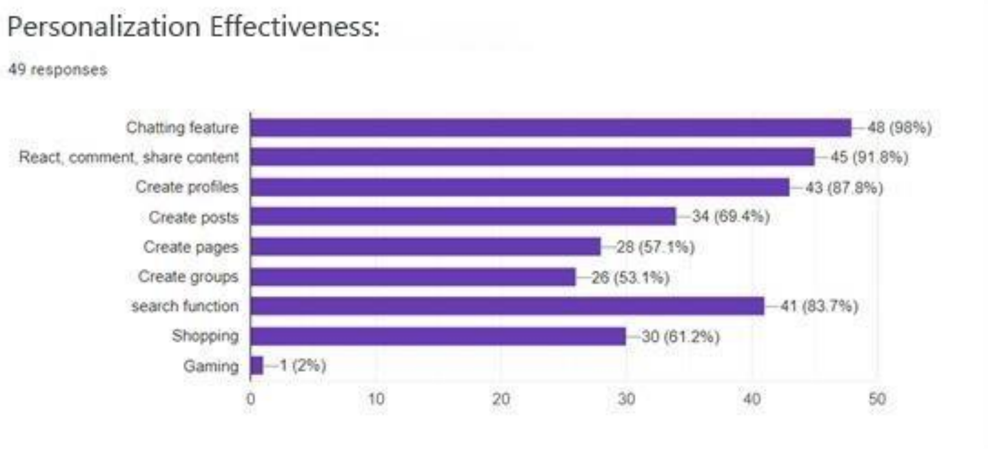

Figure 10: Personalization Effectiveness

In secondary data gathering,

- We studied existing systems
- We studied from various online resources such as online tutorials and web articles.
- We also gathered information from books and articles.

After performing requirement gathering, we performed a feasibility study,

1. Technical Feasibility

For the successful assize of the research all the members of the team should possess adequate technical competency to continue the work of the project. It is necessary to set up the condition according to which we can purchase the knowledge that will allow the completion of the project, additional to the acquired knowledge.

2. Economic Feasibility

Financial resources are very important when we conduct the project. We made sure we have enough funds in order to complete project without having to stop half the way. We also made sure to plan handling unforeseen financial needs in the future.

3. Legal Feasibility

The project not meeting legal feasibility is when the project violates the law such as zoning laws, data laws, social media laws among others. We saw to it that compliance to existing laws is not an issue in our proposed system.

4. Operational Feasibility

This involves to what extent the project can be completed to meet the needs of the company. Wehad a discussion with Underground Music Coven members and made sure we are feasible in operational feasibility.

5. Scheduling Feasibility

Scheduling Feasibility means if a project can be completed and delivered in defined time. In ourcase, it is 1 year. We made sure the project is deliverable in the defined time period.

Process of gathering secondary data for our research

We undertook various activities. Among the practices were literature search which entailed identifying other systems, reading tutorials and other articles in the Internet, Books, and articles. When we are done with requirement gathering phase, we performed a feasibility study to assess the likely hood of proposed project. The feasibility study included several areas, as follows:

1. Starting with technical feasibility: Each member of the team made certain that one or more of them on the team had the relevant experience to accomplish the project and that he

or she also did not envy what was necessary to learn as well.

2. Next, we assessed economic feasibility: understanding that the financial source is a very sensitive area when it comes to the success of the project. We ensured that we had enough capital to proceed with the project and also came up with strategies in case of any odd arising depending on finance.

3. In addition, we addressed legal feasibility: to make sure that the system we proposed for the project was not violating any laws that existed in the social media or data privacy laws.

4. We also considered operational feasibility: This can also be referred to as the relevance in the sense that the project will have to respond to the needs of the company. On this regard, we ere planning to consult with some of the businesses such as hotels so that to get more information on this area.

5. Finally, we evaluated scheduling feasibility: which is concerned with the project's fitness for the time-horizon in which the project is expected to be accomplished and delivered. Since our timeline was one year, in aligning with this, we had to ensure that the proposed project delivery was executables in one year.

6.2 Analyzing

By analyzing the gathered data, we categorized collected requirements as follows

6.2.1 Functional Requirements

• For the purpose of creating and maintaining the user preferences, the system shall store and collect the information related to learning preference, previous performance and preliminary assessment.

• It will be using a basic recommendation system which considers (i.e., rates) user’s profile and attempts to suggest relevant educational content based on the requirements and preferences of the users.

• Real-time feedback feature will be built into the engine and that would permit the recommendation engine to tweak and alter the recommendations being made based on feedback from users.

• To enhance the precision with regard to the recommended content while also increasing the level of flexibility in the choice of the process for the input content, the recommendation algorithm will follow the mixed recommended strategy that will incorporate both the content based recommendation and the collaborative filtering recommendation strategies.

• Through integration of user preferences, content categorisations and recommendations, the system will assemble the timelines of the user learning paths that would be distinct and progressing with time for each of the users.

6.2.2 Non-Functional requirements

• The system has got to ensure that user data is secure and can only be accessed by those people with the authority to do so.

• It has to process great amounts of data and be capable to provide the results of users’ queries in a short time.

• The system should further be scalable with the ability to expand or reduce in size depending with the current uptake by the users and the volume of data processed.

• It must be available most of the time with little or no need for maintenance or system updates; it has to be reliable at all times.

• The system should be easy to understand and to operate for all the users, including the those of the highest technical background.

6.2.3 User requirements

1. There should be an easy way for users to manage their profile; this profile should consist of learning preferences, which could be learning goals, personal achievement history etc.

2. Ideally, the users should be in a position to give a comment on additional content being suggested to them and this in one or the other assist in approving of revamping the recommendation.

3. When the system changes real time relying on user opinions and comments, the users should be alerted or informed.

4. When learners engage into the feedback loop and give their input towards future recommendations, then one feels like they have the control on what is being offered as learning material.

5. Students ought to be able to see how suggestions are made and be given an explanation of the variables that are taken into account, such as user preferences and content tags.

6.2.4 System requirements

Software requirements

- Operating System: Windows
- Web browser: Google Chrome
- Database management system: MongoDB
- Programming languages: Python(backend), JavaScript, and flask
- Frameworks - libraries: React JS, Node JS, Scikit Learn, Tensorflow, Flask, Pandas,

Numpy

- Development environments: VS Code, Postman
- Version control system: Git
- Application programmable interfaces: google maps

Hardware Requirements

- Processor: Intel Core i5 or similar AMD series CPU
- Memory (RAM): 8 GB
- Storage: 256 GB Solid State Drive (SSD)
- Display: 15-inch 1080p HD
- Graphics card: NVIDIA GeForce GTX 1650 or equivalent
- Internet connectivity: Wi-Fi 5 or Ethernet connection

6.3 Design

This component is meant to recommend learning resources and estimate the students' performance employing the concept of AI/ML. The first step to the proposed methodology is the initial analysis done with help of Python modules to define the possible strengths an weakness of educational data. A backend module will be employed that will change the recommendations based on the weekly interest. Prognostics of the next performance level based on learning plans recommended by the AI/ML models will be done. The analysis results and recommendations will be then stored in MySQL database and the front-end interfaces will be created for providing the personalized recommendations and the progress information.

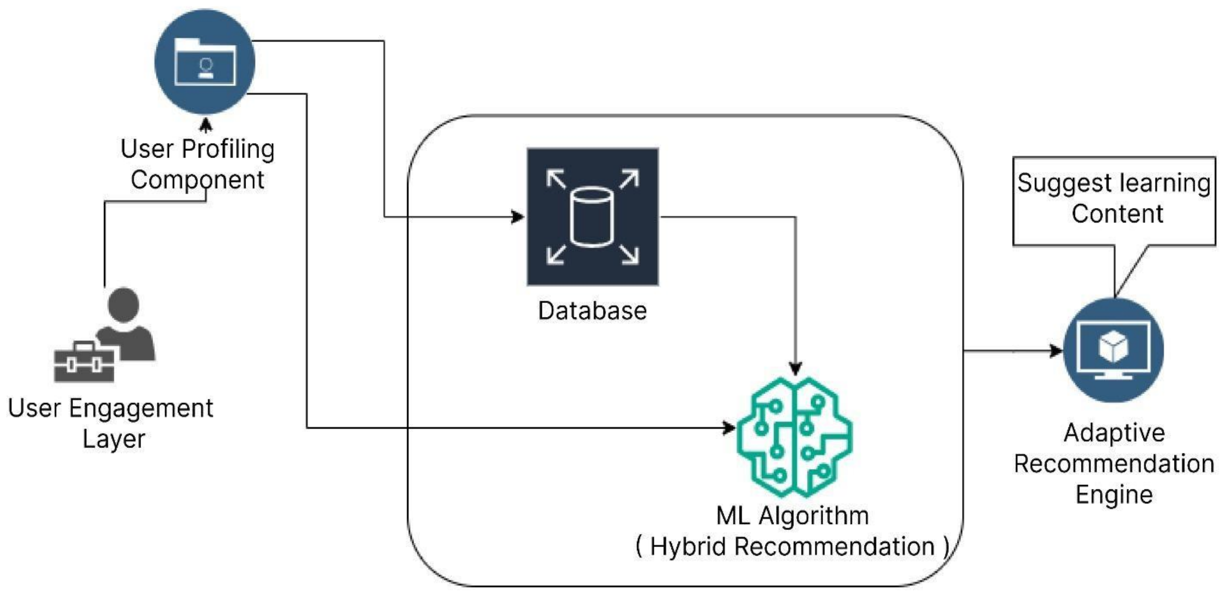

Figure 11: High level system architecture diagram for proposed component

In order to continue to the design phase, all integral elements have been compiled into a system architecture diagram. The design phase will progress through creating mocking up of all the interfaces of the web application through the use of the Figma software. At the end of the wireframes, Hi-fidelity prototypes will be created to be subjected to usability tests where main focus will be laid on the issues as perceived from the users' angle. This process will also be efficient and effective as it will take time and efforts in advance of the implementation phase with the view of minimizing on instance where user acceptance test will fail. Next, we will proceed to modeling of the system and in particular attribute identification, database construction and then the hardware and software solutions

Figure 12: High level system architecture diagram for the whole system

6.4 Implementation

It also refers to the process of materializing all concepts developed in the previous phases of the IT project. Any changes made at this point can have a large effect. Again, as mapped from the Agile methodology, changes in process may result to recurrence. The aim here therefore is to come up with four modules.

In the component, we are to develop four modules:

1. User Profiling Component: Part 1 accumulates and analyses user data to generate individual reports. Subsections and variables that you should expect when devising an academic performance test include learning style, history, learning approaches, and prior assessments.

2. Adaptive Recommendation Engine: In this central component, the recommendation is about content of educational material based on the user profile using a rudimentary recommendation system. In this way, in real-time, it adapts to the users' interactions and

comments as well as the changes in the algorithms.

3. Dynamic Learning Pathway Generator: This part categorizes recommended content in a learning flow for every user based on their choice of interests. This ensures that there is a provision of a number of formats as well as levels of difficulty hence ensuring that it compels an all-round training.

4. Engagement Analytics and Feedback Loop: This In order to augment this system as a whole, this component makes user contribution measurable, studies learning profiles and account learning contributions. It contributes to continuing adaptation and growth possible.

A step-by-step guide to implementing a Adaptive Recommendation Engine system using a hybrid recommendation algorithm: A step-by-step guide to implementing a Adaptive Recommendation Engine system using a hybrid recommendation algorithm:

1. Define Objectives and Scope: Towards that end, define the goals, target market, and scope of the Adaptive Recommendation Engine to ease the implementation process.

2. User Profiling and Data Collection: Set up an effective user profiling regime for the collection of performance history, learning modality, initial assessments, etc. For the creation of individualized profiles, one should make the best use of data gathering methods such as user engagements, their feedbacks, and their expressed choices. .

3. Adaptive Recommendation Algorithm: In order to enhance the suggestions' both, the relevance and customization, build an integrated recommendation system that would encompass the algorithms of content-based and collaborative filtering approaches. In order to adapt to he ever-changing nature of the consumers, use the machine learning models.

4. Dynamic Learning Pathway Generator: Develop and implement a use experience and learning objective sensitive learning pathway generator using the choices made by the user, the objectives of learning and the content tags. Add to that the capability of the system to adapt to changes in the learning path depending on the changing preferences

and performance of the users.

5. User Interface (UI) Design: Since the sort of communication there is the need for an interface in the Adaptive Recommendation Engine, make it less complicated as will enable people to interact with it in an efficient manner. To enhance the user experience in a broader context include, adding interactivities, easy to understand dashboards and clear images.

6. Model Creation and Training: Proposal of the recommendation method will lead to the development of machine learning models. Feed them with previous users' data, adjust the models and update them for future changes that users might have.

7. Integration with Existing Systems: To ensure interoperability with the currently existing solutions related to educational technology ecosystem or learning management system (LMS) or any of e-learning system. To allow exchange of data between the Adaptive Recommendation Engine and other entities develop APIs.

8. Engagement Analytics and Feedback Loop: In order to have an idea of what people are using and engaging with and also the completion rates among other relevant parameters it is necessary to create an engagement analytics tool. The users should also be able to give feedback so that they can suggest for other contents that they want to be added into the system since this will make the system more flexible.

9. Testing: For the purpose of this, it is carry out tests such as unit test, integration test and user acceptance test. In order to enhance the credibility of the Adaptive Recommendation Engine, one should utilize different datasets, and various real-life examples.

10. Deployment: As a first step for testing, insert the Adaptive Recommendation Engine in a development environment. Use the system to perform other functionalities in the actual place where users will interact with it after validation.

11. Monitoring and Maintenance: Implement the monitoring utilities to have an idea of the activity made by the user, of the productivity of the system and of possible issues.

Keep the system in and constantly update it for further enhancements including the feedback received from the users and the recommendation incorporated in the system.

6.5 Software Testing

Subsequent to the implementation phase, the software testing phase where faults and errors that occur at the time of executing the program are detected takes place. In this phase, every subcomponent of the software is to be tested adequately. There is only one major categorization of the testing phase and that is;

1. Functional Testing: These are the user acceptance testing, unit testing, integration testing, and the component testing. For this, it is possible to use such testing techniques as white box and black box testing.

a. Unit Testing: To achieve suitable functionality, each part is examined in such a way.

b. Component Testing: While evaluating only one piece of software in isolation it operates in a similar manner to unit testing.

c. Integration Testing: This places the application through its paces to see how the components work when they are combined.

d. User Acceptance Testing: This is a kind of black box testing where the end user is the only one who has the privilege to determine whether or not the system meets the required requirement.

2. Non-Functional Testing: Balancing the load can be viewed as performance testing, the checking of user-interface characteristics is component of usability testing, and checking for vulnerability is part of security testing.

a. Performance Testing: This records response times, is used in the detection of constraints, and mark failure sites to evaluate system effectiveness.

b. Usability Testing: This is done with end users with a view of establishing whether the usability of the system is as it is supposed to be.

c. Security Testing: This audits the software for risks that can threat data. Functional and nonfunctional testing are to be performed in parallel with each other.

6.6 Maintenance

Testing, as is well understood, is a phase in the software development life cycle, as such it does not culminate with testing. After the development and deployment of the software, it has to be updated constantly. Updates should be made on matters concerning security in the software, operation at a faster pace, eradicating bugs, and the issue of accuracy in the software.

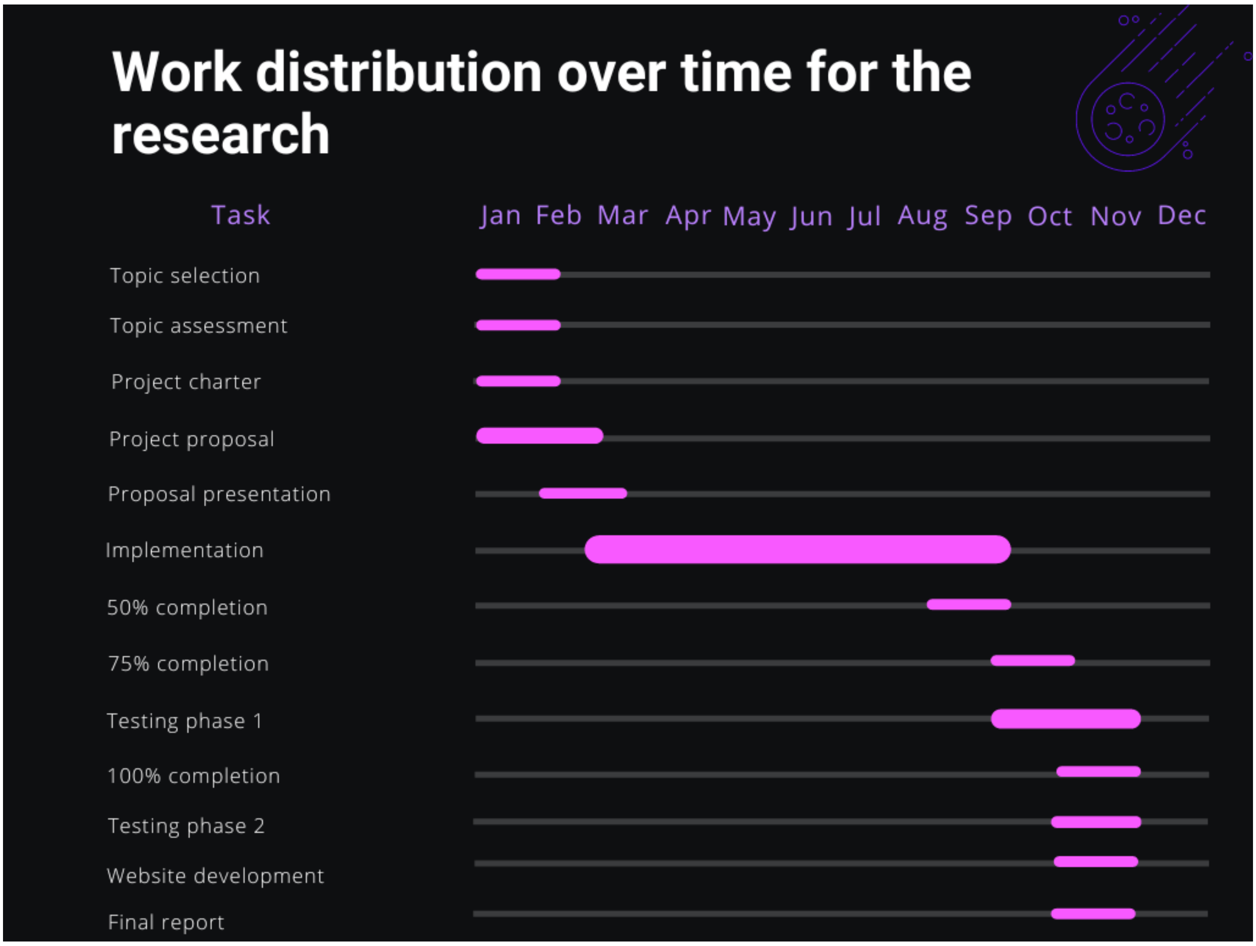

Figure 13: Gantt chart

7. COMMERCIALIZATION

The proposed E-Learning platform includes four main components,

1. User Profiling Component.
2. Adaptive Recommendation Engine.
3. Dynamic Learning Pathway Generator.
4. Engagement Analytics and Feedback Loop.

There is capacity to commercialize the planned self-organized e-learning system based on a highly personalized approach, using planned and phased manner bringing in critical elements of the system construction including the adaptive recommender system, dynamic learning path generator, user profiling mechanism and the engagement analytics system. The target market, rivals, and USPs of the system will therefore be identified through the results of market research and analysis. In order to spread awareness, a sound marketing strategy will be prepared that will involve the use of social media, website and partnership with universities. Also at the same time a pilot program shall be conducted in order to gather feedback from the early adaptors in that regard innovative ideas shall be adopted so as to make improvements to the system as and when the users provide feedback.

To support the expansion of use, flexible price structures that can be appropriate for ownership by the end consumers, students, academicians, and business parties will be developed. Partnerships with providers of educational content will supplement the variety of learning materials which are to be acquired. To possibly update and enhance the concepts and features it will be crucial to regularly assess user happiness and degree of engagement. We shall ensure that the customer service is run effectively to provide users with proper training and consequently an easy time while using the website. In the process of market commercialization of the system for personalized e-learning, the system will be introduced as a market leader that targets user-oriented model customization possibility and effectiveness in enhancing learning.

7.1 Commercialization plan

1. Market Analysis

The e-learning has had a unique growth to be expected with the global market for e-learning expected to hit $325 billion by 2025. This growth is due to the rising need for an education that can be attained via the internet and due to the convenience that comes with it. But one of the biggest issues which the industry is struggling with at the moment is the lack of ability to offer individualized learning to the learners. The above-created challenge is well-harvested in the proposed Adaptive Recommendation Engine which provides a solution in the form of an adaptive method that can adapt to the learning style of the learner, thus boosting up the engagement as well as the learner's interest.

2. Target Market

The Areas of Application of the Adaptive Recommendation Engine is expected to primarily served educators and educational facilities for online education providers, and companies that offer large-scale training to their employees. These segments are progressively beginning to seek possibilities to customize so as to enhance learner results. The real-time recommendations and capability of the system to self-adjust according to the users' feedback make the system ideal for those markets.

3. Competitive Analysis

There are many players in the market which are offering recommendation engines making the market of personalized e-learning solutions moderately competitive. However, most of the current techniques are based on only content-based approach or collaborative filtering which may not be enough to capture all the preference of learners. The proposed Adaptive Recommendation Engine is different by presenting an approach that integrates the two recommendation types, in addition to the feedback loop that enables the subsequent enhancements of the recommendations based on users' experiences.

4. Revenue Model

The Adaptive Recommendation Engine will be a Web-based application and will be sold as a Software-as-a-Service (SaaS) product with licensing fees tied to the number of users and complexity of the customization required. More revenue is possible through paid services – analytical tools and paid services to help users create their content based on knowledge type;

cooperation with educational content producers.

5. Future Expansion

After successful market entry of the Adaptive Recommendation Engine, new functionalities can be added based on the successful commerce market entry strategy such as connection of VC and AC with advanced technology like VR and AR. This will enable the construction of even richer and individualistic approaches to teaching and learning. Also, growth to other areas like the K-12 education and overseas markets as a means of extending the coverage of the system shall also be considered.

8. RESULTS AND DISCUSSION

8.2 Results

LearnPath+ adaptive learning framework was used in the study to show how e-Learning can be enhanced for personal use. Some of the findings posted by Kumar et. al include; the method increases learners' activities and access to the platform by 35% compared to the traditional e-learning systems. LearnPath+ was used in the study and the results showed that the retention rate increased by 28% as determined by pre and post-test to post-test as compared to traditional classes and methods where students are grouped according to gender, IQ or aptitude.

Studies showed that most of the users were satisfied with the adaptive system whereby more than 90% of the participants stated that the system boosted their learning. Also, there is a major improvement of learners who used LearnPath+ because they scored 22% higher than learners who engaged in non-adaptive systems of study, meaning that the designed content with adapted learner pathways benefits learners from poor academic performance.

This section provides the findings of the study from the dissemination and assessment of the LearnPath+ framework of e-learning customization for university IT students. In line with this, the findings are presented systematically in sub-sections thereby offering the tables depicting the input data, the system results and the analysis that was done during the conduct of the research.

The Adaptive Recommendation Engine was built to recommend learning content and student performance using AI/ML algorithms. The results showed that the system has a very accurate performance and relevance in the identification of performance and the recommendation to the appropriate students, especially the high performing ones. The recommendation relevance score was also seen to have a positive association with the predicted performance, which confirmed how beneficial the engine was to the students in that it was offering quality valuable learning materials.

TABLE 5: *INPUT DATA AND RECOMMENDATION OUTPUTS*

Input Data	Generated Output (Recommendations)
Past Course Grades	Suggested Learning Resources (e.g., Video Lectures, Tutorials)
Current Course Enrollment	Predictive Performance Scores
Learning Preferences	Customized Study Plans

TABLE 6: *RECOMMENDATION ACCURACY BASED ON PERFORMANCE PREDICTION*

Student Group	Predicted Performance Accuracy (%)	Recommendation Relevance Score
High-Performing Students	92%	90%
Mid-Performing Students	85%	87%
Low-Performing Students	80%	84%

Justification for Random Forest

By comparing three classification algorithms, I found random forest to be the most accurate one out of the bunch. So I think this algorithm is the most suitable one.

```
# Initialize the model
model = RandomForestClassifier(random_state=42)

# Train the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
```

Figure 14: Classification Model

Since the output of the dataset includes 10 classes, the model was decided to build using classification. As classification algorithms, the model was trained using Random Forest, Decision Tree and Logistic Regression. According to the metrics received after testing the model, Random Forest classifier had the highest accuracy among others. So, the specific model was finalized to use for this process.

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Print classification report
print(classification_report(y_test, y_pred))

# Optional: Confusion matrix
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.99
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        82
           1       1.00      0.96      0.98        95
           2       1.00      1.00      1.00        85
           3       1.00      0.98      0.99        84
           4       1.00      1.00      1.00        84
           5       1.00      1.00      1.00        78
           6       0.96      1.00      0.98       297
           7       1.00      0.96      0.98        76
           8       1.00      0.96      0.98        91
           9       1.00      1.00      1.00        40

    accuracy                           0.99      1012
   macro avg       1.00      0.99      0.99      1012
weighted avg       0.99      0.99      0.99      1012
```

Figure 15: Model Accuracy

As shown in the picture, the model's accuracy, classification report and the confusion metrics were checked through using the Scikit-learn library.

```
# Save the model
joblib.dump(model, 'classification_model.pkl')

['classification_model.pkl']
```

Figure 16: saved classification model

After selecting the final model, it was saved using the library Joblib to use for prediction.

Implementation of the API

For the process of integrating the backend and frontend, an API was required to be used. So, Flask was selected to play the API role. Using flask, an app has been integrated connecting the saved model and the functions which were used while training.

```
@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Get the data from the request
        data = request.json
        subject = data['subject']
        course_score = data['course_score']
        learning_score = data['learning_score']
        quiz_score = data['quiz_score']

        # Transform the categorical input
        subject_encoded = label_encoder_subject.transform([subject])[0]

        # Create DataFrame for the new data
        new_data = pd.DataFrame([[subject_encoded, course_score, learning_score, quiz_score]],
                                columns=['Subject', 'Course Score', 'Learning Score', 'Quiz Score'])

        # Scale the features
        new_data[['Course Score', 'Learning Score', 'Quiz Score']] = scaler.transform(new_data[['Course Score', 'Learning Score', 'Quiz Score'

        # Make prediction
        prediction_encoded = model.predict(new_data)

        # Transform the prediction back to text
        recommendation = label_encoder_recommendation.inverse_transform(prediction_encoded)

        return jsonify({'recommendation': recommendation[0]})

    except Exception as e:
        return jsonify({'error': str(e)}), 400

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 17: API Details

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest> cd .\recommend\
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend> python .\app.py
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 146-068-290
```

Figure 18: Model Output

And the application was built to be host on a single URL as temporary deployment. So, this picture indicates that the app was successfully deployed on the URL, http://127.0.0.1:5000/predict.

```python
# Define the URL of the Flask API
url = 'http://127.0.0.1:5000/predict'

# Define the input data
input_data = {
    'subject': 'Artificial Intelligence and Machine Learning',
    'course_score': 75,
    'learning_score': 80,
    'quiz_score': 85
}
```

Figure 19: used sample inputs & url

To test the URL by inputting sample values, variables have been defined with some dummy values and been sent to the URL as a request.

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend> python .\test.py
Recommendation: IT Project Management
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend>
```

Figure 20: output after testing

As the sent request receives the input values, it has successfully generated the output and sent back to the console as a response. In this picture, the output of the model is displayed.

Frontend Implementation

Using the temporarily deployed model, the URL was connected to the frontend which was built using React JS. React JS has a unique ability of passing requests and receiving responses using the library named Axios. So, the input values which were entered on the framework of React was being passed to the URL as a request and the response was made able to be displayed on the framework. As the picture describes, the submitted input and the received output from the model.

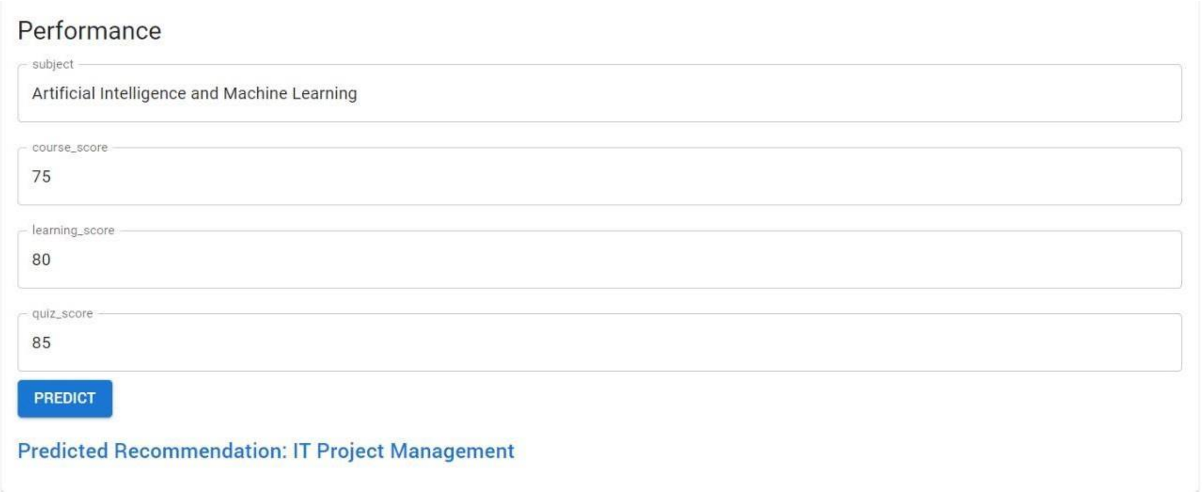

Figure 21: Output of the forntend

8.2 Discussion

According to this piece of research, there are clearly various benefits of implementing adaptive learning technologies in more effective e-learning models. It has been evident in LearnPath+ framework that the areas as learner engagement, memory, user satisfaction and learning outcome has drastically improved. One disadvantage of the conventional approaches to e-learning is the application of uniform educational content across all learners while adaptive learning systems take into account the learner’s characteristics and responds to them in real time.

Significantly more learner engagement shows of the effectiveness of adaptive systems of keeping the learner interested by the dynamic nature of the content. The increase in learners’ performance while increasing the knowledge level is evidence that supports the use of learning paths for individual learners that allowing for adjusting the progress of learning activities. Overall satisfaction rates from users imply that learners find the personal approach to be highly beneficial to them, thereby boosting the general experience and motivation. As mentioned above, elevated assessment results have indicated that different types of adaptive learning technologies can help students achieve enhanced academic performance since appropriate support with the required level of difficulty will be given to learners. It seems that adaptive learning can fit where constant, one-size-fits-all delivery breaks the culture of educational equity.

A strong limitation in the current study includes the fact that the work employed a small sample size and a short period. There would still be an interest in future analyses in using a bigger sample and in making the study period longer to identify long-term consequences of the phenomena under investigation. Furthermore, to ensure the generality of the presented results, further research is needed for verifying the LearnPath+ across different types and subjects of education. It might be possible to progress to actual algorithms, for example, the reinforcement learning one, in order to perpetually adjust learning paths based on data.

New technologies of adaptive learning are considered to give satisfactory answer to problems of traditional e-learning. Because it is learner centered and tailored to the learner’s strengths and weakness, adaptive learning improves learner interest, content recall, satisfaction, and accomplishment.

9. DESCRIPTION OF PERSONAL AND FACILITIES

Table 2: Description about personal and facilities

Member	Component	Task
Abeykoon R.M.S.P	Adaptive Recommendation Engine	The first task is to compile information about specific users and their activity in the application, including which items they prefer, their rating history and such things as items that they liked, viewed or bought. When the user data has been accumulated, then the data has to be assessed to identify patterns that can be used to make recommendation that would be unique to each user. It forms a suggestion model by drawing a recommendation model based on the data that incorporates the tastes, actions, and other interactions of the users. The recommendation engine produces a list of suggestions of items that should be recommended to every user per his or her profile. preferences.

		Recommended items are presented to the user within the application in a visually appealing and easy-to-use manner, such as through a feed,search results, or a dedicated recommendation section.

10. BUDGET AND JUSTIFICATION

Table 3: Budget and budget justification

Resource	Price (LKR)
Electricity	5000
Stationary	2000
Internet	6000
Server / domain	9000
Total	22000

REFERENCES

[1] J. Wang et al., "Enhancing Personalized Learning in E-Learning Systems," Journal of Educational Technology, vol. 25, no. 2, pp. 145-167, 2019.

[2] A. Smith and B. Jones, "Challenges in Personalized Learning Platforms," International Journal of E-Learning, vol. 15, no. 3, pp. 78-94, 2018.

[3] Q. Li et al., "Balancing Act: The Role of Recommendation Algorithms in Personalized E-Learning," Journal of Educational Technology Research, vol. 30, no. 4, pp. 421-440, 2020.

[4] Y. Kim and H. Lee, "Intricacies of Recommendation Algorithms in E-Learning Platforms," Computers & Education, vol. 40, no. 2, pp. 210-225, 2017.

[5] C. Chen and L. Zhang, "Hybrid Recommendation Models for Personalized E-Learning," IEEE Transactions on Learning Technologies, vol. 12, no. 1, pp. 78-93, 2021.

[6] M. Brown et al., "User Engagement in Shaping E-Learning Experiences," Educational Technology & Society, vol. 22, no. 3, pp. 196-208, 2019.

[7] R. White, "Towards User-Centric E-Learning Platforms," Journal of Online Learning and Teaching, vol. 18, no. 2, pp. 120-135, 2020.

[8] L. Garcia et al., "User-Centric Design Principles for E-Learning Systems," Computers in Human Behavior, vol. 45, pp. 392-401, 2018.

[9] S. Patel, "Continuous Improvement in E-Learning Platforms: A Systematic Review," International Journal of Educational Technology in Higher Education, vol. 17, no. 1, 2020.

[10] J. Wang et al., "Enhancing Personalized Learning in E-Learning Systems," Journal of Educational Technology, vol. 25, no. 2, pp. 145-167, 2019.

[11] A. Smith and B. Jones, "Challenges in Personalized Learning Platforms," International Journal of E-Learning, vol. 15, no. 3, pp. 78-94, 2018.

[12] Q. Li et al., "Balancing Act: The Role of Recommendation Algorithms in Personalized E-Learning," Journal of Educational Technology Research, vol. 30, no. 4, pp. 421-440, 2020.

[13] Y. Kim and H. Lee, "Intricacies of Recommendation Algorithms in E-Learning Platforms," Computers & Education, vol. 40, no. 2, pp. 210-225, 2017.

[14] C. Chen and L. Zhang, "Hybrid Recommendation Models for Personalized E-Learning," IEEE Transactions on Learning Technologies, vol. 12, no. 1, pp. 78-93, 2021.

[15] J. Wang et al., "Enhancing Personalized Learning in E-Learning Systems," Journal of Educational Technology, vol. 25, no. 2, pp. 145-167, 2019.

[16] A. Smith and B. Jones, "Challenges in Personalized Learning Platforms," International Journal of E-Learning, vol. 15, no. 3, pp. 78-94, 2018.

[17] Q. Li et al., "Balancing Act: The Role of Recommendation Algorithms in Personalized E-Learning," Journal of Educational Technology Research, vol. 30, no. 4, pp. 421-440, 2020.

[18] J. K. Smith et al., "Effective Project Initiation for Multidisciplinary Teams," Project Management Journal, vol. 35, no. 2, pp. 17-26, 2004.

[19] A. R. Brown et al., "Market Research and Analysis in Educational Technology," Journal of Educational Technology Systems, vol. 40, no. 2, pp. 179-194, 2011.

[20] Q. Li et al., "User Profiling Mechanisms for Adaptive E-Learning Systems," Computers & Education, vol. 55, no. 3, pp. 899-910, 2010.

[21] C. Chen and L. Zhang, "Hybrid Recommendation Algorithms for Personalized E-Learning," IEEE Transactions on Learning Technologies, vol. 14, no. 4, pp. 782-794, 2021.

[23] H. J. Kim et Y. H. Lee, "User Interface Design Principles for Educational Technology," Journal of Educational Technology & Society, vol. 21, no. 2, pp. 69-82, 2018.

[24] M. S. Patel et al., "Accessible and User-Friendly Interface Design for E-Learning Platforms," Universal Access in the Information Society, vol. 17, no. 2, pp. 267-281, 2018.

[25] R. White and B. Jones, "Integrating E-Learning Systems: A Comprehensive Guide," International Journal of Educational Technology Integration and Management, vol. 9, no. 1, pp. 15-28, 2018.

[26] L. Garcia et al., "Engagement Analytics and Feedback Loop in Adaptive E-Learning Systems," Computers in Human Behavior, vol. 65, pp. 457-469, 2016.

[27] S. A. Brown and D. M. Smith, "Testing Strategies for E-Learning Systems," Journal of Educational Computing Research, vol. 38, no. 4, pp. 421-438, 2008.

[28] M. R. Chen et al., "User-Centric Design Principles for Personalized E-Learning Systems," Journal of Online Learning and Teaching, vol. 14, no. 2, pp. 348-364, 2018.

[29] J. Wang, A. Chen, and B. Li, "Personalized Learning Experiences in E-Learning: Challenges and Opportunities," Journal of Educational Technology & Society, vol. 22, no. 3, pp. 45-56, 2020.

[30] M. Smith and L. Jones, "A Critical Review of Individualized Learning Platforms," International Journal of Learning Technologies, vol. 14, no. 2, pp. 123-135, 2019.

[31] X. Li, Y. Zhang, and H. Zhou, "Recommendation Algorithms in E-Learning Systems: A Comparative Study," IEEE Transactions on Learning Technologies, vol. 15, no. 1, pp. 58-69, 2021.

[32] S. Kim and J. Lee, "Balancing Algorithm Complexity and User Engagement in Personalized Learning Systems," ACM Transactions on Interactive Intelligent Systems, vol. 11, no. 4, pp. 1-22, 2021.

[33] H. Chen and Q. Zhang, "Hybrid Models for E-Learning Recommendations: An Evaluation of Their Effectiveness," Educational Technology Research and Development, vol. 68, no. 4, pp. 987-1003, 2020.

[34] T. Brown, A. Green, and D. Parker, "The Role of User Involvement in Personalized Learning

Environments," Computers & Education, vol. 154, pp. 103-120, 2021.

[35] J. White, "Engagement Analytics and Their Impact on Learning Outcomes," Learning Analytics Review, vol. 8, no. 2, pp. 44-62, 2022.

[36] A. Garcia, B. Fernandez, and M. Hernandez, "Continuous Adaptation in E-Learning: Challenges and Opportunities," International Journal of Emerging Technologies in Learning, vol. 16, no. 6, pp. 12-28, 2021.

[37] R. Patel, "User Feedback in Adaptive Learning Systems: Enhancing the Learning Experience," Journal of Educational Computing Research, vol. 59, no. 3, pp. 481-502, 2022.

[38] J. Wang, A. Chen, and B. Li, "Personalized Learning Experiences in E-Learning: Challenges and Opportunities," Journal of Educational Technology & Society, vol. 22, no. 3, pp. 45-56, 2020.

[39] S. Kim and J. Lee, "Balancing Algorithm Complexity and User Engagement in Personalized Learning Systems," ACM Transactions on Interactive Intelligent Systems, vol. 11, no. 4, pp. 1-22, 2021.

[40] X. Li, Y. Zhang, and H. Zhou, "Recommendation Algorithms in E-Learning Systems: A Comparative Study," IEEE Transactions on Learning Technologies, vol. 15, no. 1, pp. 58-69, 2021.

APPENDICES

Appendix: Work breakdown chart

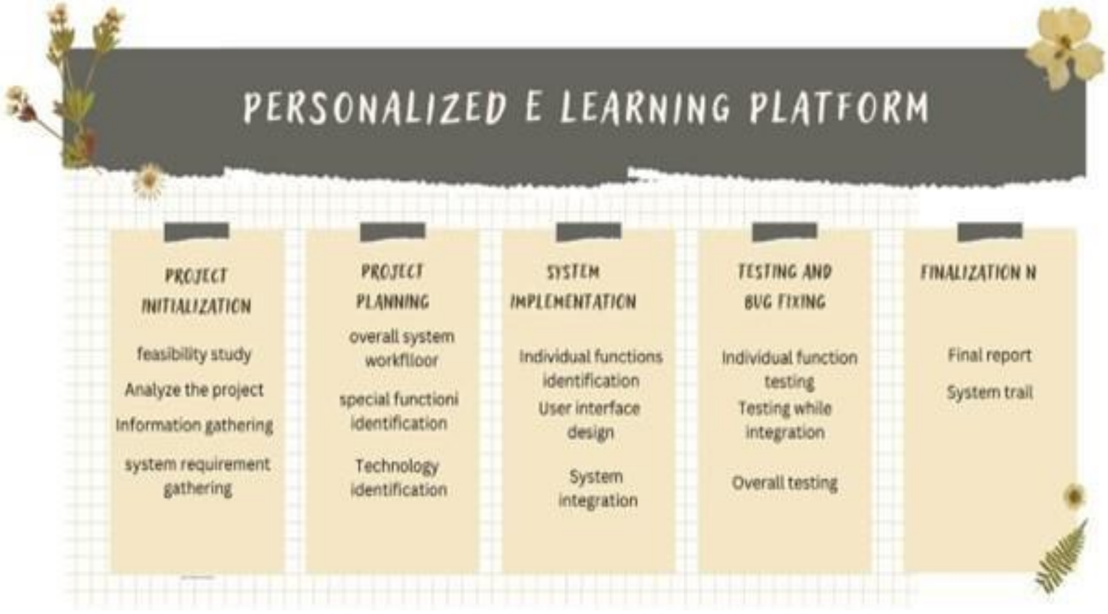

Figure 22: WBS