ENHANCING PERSONALISED E-LEARNING

Project ID: R24-112
Project Proposal Report

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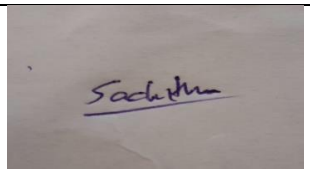
DECLARATION OF THE CANDIDATE AND SUPERVISOR

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 not contain 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.

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Ms.Sanjeevi Chandrasiri Date

ABSTRACT

In order to get over the drawbacks of the existing personalized e-learning systems, the Adaptive Recommendation Engine is a ground-breaking solution. The primary goal of this cutting-edge system's design is to prioritize user engagement and simplicity while integrating adaptive machine learning to deliver a truly customized learning experience. A sophisticated hybrid recommendation approach is integrated into the core architecture of the engine, combining content-based and collaborative filtering algorithms in a harmonious way. Because of this dynamic methodology, the system can respond to user interactions and feedback by suggesting and adjusting learning content in real-time. The incorporation of a dynamic learning pathway generator is a crucial element of the design, guaranteeing that learning pathways are not only customized but also dynamically adjust in response to individual performance and preferences.

An essential part of the process is user profiling, which creates personalized profiles by evaluating a variety of data sets, including past performance metrics, learning preferences, and initial assessments. In addition, a feedback loop and an engagement analytics system monitor and analyze user interactions and completion rates. By allowing users to actively shape their educational experience, this system promotes empowerment and teamwork. The Adaptive Recommendation Engine is notable for its novel approach to interpretation, achieving a careful equilibrium between algorithmic intricacy and user-centered design. Maintaining this balance is essential to providing individualized e-learning experiences that are both efficient and interesting. To sum up, this study presents a fresh and thorough approach to the body of current knowledge. The field is moving toward more efficient and captivating personalized e-learning solutions thanks to the Adaptive Recommendation Engine, which is a major advancement that seamlessly integrates adaptive machine learning, user-centric design, and advanced analytics. It provides a useful and approachable method for improving user engagement, knowledge retention, and general satisfaction in online education in addition to filling in existing gaps in the literature.

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LIST OF ABBREVIATIONS

GUI	Graphical User Interface
API	Application Programming Interface
IT	Information Technology
WBC	Work Breakdown Chart

1 INTRODUCTION

The aim of the present study is to investigate the shortcomings of existing e-learning platforms in terms of providing customized learning opportunities. Current platforms often rely on generic techniques and lack flexibility for unique user preferences. By offering a user-centric strategy that combines adaptive machine learning with an easy-to-use interface, the initiative seeks to close this gap. The goal is personalized learning experiences that are accessible and effective. The goal of the project is to develop a system with an adaptive recommendation engine, dynamic learning path generator, user profiling component and engagement analytics using insights from machine learning, educational technology and user experience design. The ultimate goal is to advance the field by introducing a new strategy for more efficient and engaging personalized e-learning solutions.

1.Existing e-learning platforms

Current e-learning platforms, which include popular ones like Moodle, Blackboard, Canvas, edX, and Coursera, provide a variety of options for online learning. To help spread instructional information, these platforms make use of Learning Management Systems (LMS), content delivery networks, video streaming, and evaluation instruments. Although remote learning is convenient, there are still some frequent dangers to be aware of. These include confusing user interfaces, a lack of genuine customization, and limited flexibility to individual learning preferences. Users' responses to these platforms differ; some thank them for being accessible, while others express annoyance at the complexity of the interface. From sophisticated multimedia delivery systems to conventional LMS frameworks, a variety of technologies are used. Comprehending the advantages and disadvantages of contemporary e-learning platforms is essential for the ongoing enhancement of online learning and the creation of novel remedies for existing inadequacies.

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

2 Loop faults of the existing systems

Current e-learning platforms face many serious issues that affect the user experience. Personalized learning experiences are lacking in common loop errors, since generic techniques frequently fall short of accommodating individual preferences. Intricate user interfaces impede smooth navigation by causing dissatisfaction in the user. Insufficient flexibility presents difficulties since systems find it difficult to dynamically adapt to changing user requirements, which leads to a stagnant learning environment. Moreover, inadequate engagement data make it difficult for instructors to monitor user interactions and make improvements to their curriculum. Inadequate user engagement methods, including feedback loops, impede cooperation and active participation. Together, these loop defects exacerbate user unhappiness and underscore the need for creative solutions in the e-learning space.

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

The suggested Adaptive Recommendation Engine introduces novel features to improve the overall user experience while methodically addressing the loop errors common in current e-learning systems. With an emphasis on user involvement and simplicity, the platform addresses the deficiency of tailored learning experiences present in many existing solutions. By including a dynamic learning route generator, which modifies individualized learning paths depending on user performance and preferences in real-time, the static character of traditional platforms is lessened, and flexibility is ensured. The hybrid recommendation technique solves the drawbacks of generic approaches by combining content-based filtering algorithms with collaborative filtering to provide a more personalized and nuanced learning experience. A feedback loop method addresses the low user engagement in current systems, encourages cooperation, and allows users to actively shape their educational path. Sturdy engagement metrics enable instructors to make ongoing improvements to the course material by giving them useful information about user interactions and completion rates. The Adaptive Recommendation Engine aims to provide a complete and user-centric solution by methodically correcting these loop defects, promoting efficient, interesting, and customized e-learning experiences.

1.1 Background survey

The purpose of the e-learning system's background survey is to determine how satisfied users are with the platform's tailored learning experiences and how they feel about the Adaptive Recommendation Engine in particular. The survey asks about the platform's overall user-friendliness, perceived personalization of content recommendations, and overall happiness. It also explores the degree of user involvement in influencing content recommendations through the feedback loop mechanism, the efficacy of the Adaptive Recommendation Engine, and the system's perceived flexibility over time. The benefits of dynamic learning pathways and user involvement with analytics are also examined in the poll. With regard to usage frequency, educational background, and open-ended comments, the survey tries to collect thorough information about user experiences, preferences, and possible areas for development. In order to better connect the e-learning platform with user needs and expectations, this survey will be an invaluable tool.

To identify the main problems and issues within the domain, and to get an overall idea about the domain such as to whom we provide this solution and how the problems diverse, we hope to conduct a google form and retrieve responds.

These are the questions to be asked in the below given survey:

1. Overall Satisfaction:
    - (How happy are you, on a scale of 1 to 10,with the whole e-learning experience that our platform has to occur)

2. Personalization Effectiveness:
    - How much do you think the learning paths and content recommendations are tailored to your requirements and preferences? (Scale: Not at all - Extremely)

3. User-Friendly Interface:
    - How easy is it for you to navigate and access the learning materials on the platform? (Scale: Not user-friendly - Very user-friendly)

4. Effectiveness of Recommendations:
    - In your opinion, how well does the Adaptive Recommendation Engine provide

recommendations for pertinent learning materials? (Scale: Ineffective - Highly Effective)

5. Perceived Adaptability:
    - How much do you think the system adjusts over time to your changing preferences for learning? (Scale: Not at all - Completely)

6. User Involvement in Recommendations:
    - Do you think the feedback loop system has allowed you to be sufficiently active in developing the content recommendations? (Yes/No)
7. Engagement Analytics:
    - How frequently do you monitor your learning progress and pinpoint areas for improvement using engagement analytics? (Scale: Rarely - Frequently)

8. Dynamic Learning Pathways:
    - How helpful do you think the dynamic learning pathways have been in directing your academic path? (Scale: Not beneficial - Highly beneficial)

9. Suggestions for Improvement:
    - Do you think any particular features or functionalities should be added or improved to improve the learning experience? (Open-ended)

10. Usage Frequency:
    - How often do you use the online learning environment? (Options: Daily, Weekly, Monthly, Rarely)

1.2 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.

1.3 Research Gap

The lack of complete solutions that effectively combine adaptive machine learning with user-centric design is a defining feature of the research gap concerning the Adaptive Recommendation Engine in personalized e-learning systems. Prior research, such that conducted by Wang et al. [10] and Kim and Lee [11], highlights how ineffectively popular e-learning platforms may adjust to the preferences of specific users. A significant research gap, however, is revealed by the lack of comprehensive strategies that actively include users in directing their educational experience while also addressing algorithmic nuances. Li et al. [12] draw attention to the current problem that certain platforms prioritize algorithmic complexity over thorough user preference analysis, emphasizing the necessity for a balanced approach in recommendation algorithms. The literature study highlights a contradiction: although some research focus on complex recommendation algorithms [13], others ignore the critical role that user preferences and participation play. Conversely, less flexible methods don't offer the flexibility needed for tailored education [14]. This difference is made even more obvious by the way the suggested system attempts to close it by providing a unique Adaptive Recommendation Engine that combines engagement metrics, a dynamic learning pathway generator, and a feedback loop mechanism. In doing so, it actively involves users in improving the recommendations for information, resulting in an e-learning environment that is both user-centric and adaptive [15].

Table 1

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

Table 1 : Proposed system compared to existing systems

1.4 Research problem

The shortcomings of present platforms in providing completely individualized learning experiences are the research challenge that motivated the development of the Adaptive Recommendation Engine within personalized e-learning systems. Because they frequently rely on generic strategies that might not maximize user engagement and information retention, existing e-learning systems frequently fail to adjust to the unique preferences of individual users [16][17][18]. The current problem is that there isn't a complete solution that combines adaptive machine learning and user-centered design in a way that makes it possible for users to actively influence their learning process. While some research delves into complex recommendation algorithms without taking user preferences into account holistically [18], other studies present oversimplified solutions that lack the flexibility needed for individualized learning [17]. The current literature gap, which emphasizes the necessity for an easy-to-use adaptive machine learning model specifically designed for tailoring learning pathways in online education, exacerbates this research dilemma [16]. By offering a novel approach that puts the user's learning journey first and combines insights from machine learning, educational technology, and user experience design, the proposed research seeks to add to the corpus of current knowledge. The ultimate objective is to

advance the sector toward more efficient and captivating customized e-learning solutions that solve the drawbacks of the available platforms and offer an instruction focused on the needs of the user.

2 OBJECTIVES

2.1 Main Objectives

The primary goal of the Adaptive Recommendation Engine sub-component is to improve the level of personalization of e-learning platform experiences by applying a simple recommendation algorithm. The system makes recommendations for learning materials based on the user's profile and modifies them in real-time with the goal of giving each user a personalized and dynamic learning experience. Contributing to the project's objective of enhancing user engagement, knowledge retention, and happiness in the context of individualized e-learning is the main objective.

2.2 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, evaluating how well user input refines and enhances the caliber of recommendations.

3 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.

In The suggested e-learning system's implementation methodology, which includes the Adaptive Recommendation Engine and all of its component modules, takes a methodical approach to meeting user and market demands. A multidisciplinary team is assembled, and specific objectives are set during the project commencement phase [19]. Key aspects and the configuration of the technology infrastructure are informed by market research [20]. Assessments and learning preferences are successfully recorded by the user profiling module [21]. A key component that combines continuous learning models and hybrid recommendation algorithms is the Adaptive Recommendation Algorithm [22]. While the UI design concentrates on developing an understandable and accessible interface, the Dynamic Learning Pathway Generator dynamically modifies paths based on user performance [23] [24]. Strong API connections enable integration with current systems [25]. The modules for feedback loops and engagement analytics allow for active modification of the learning process and increase user involvement [26]. Thorough testing guarantees system robustness before to deployment, utilizing a variety of datasets and realistic simulations [27]. Individual module accomplishments highlight the system's adaptability and efficacy by demonstrating successful implementation and adherence to user-centric design principles [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.

To complete the project, we want to apply the agile development methodology. This strategy places a strong emphasis on adaptability, teamwork, and quick iteration. It is based on the Agile Manifesto, which identifies four values: valuing people over processes and technologies, valuing working software over thorough documentation, valuing customer collaboration over contract negotiations, and valuing adapting to change over sticking to a schedule.

Agile methodologies are distinguished by brief development cycles, known as sprints, when cross-functional teams collaborate to create usable software or products. To make sure that the product satisfies their needs and that modifications can be made rapidly in response to input, the teams work closely with the customer or end-user. Continuous improvement is another key component of the agile process, which includes regular reviews and retrospectives to find areas for improvement. The seven phases of agile model.

1. Planning: This phase involves identifying the scope of the project, defining the project 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.

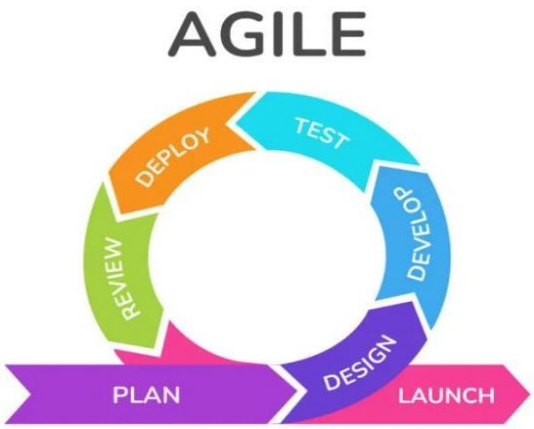
3. Design: Based on the analysis, the team designs the software or product, identifying features, functionalities, and user interfaces.

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 the software 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.



Agile model 1

Figure 1 : Agile model

3.1 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 requirement.

In secondary data gathering,

- We studied existing systems.
- We studied from various online resources such as online platforms.
- We also gathered information data sets related to component

After performing requirement gathering, we performed a feasibility study,

1. Technical Feasibility

All team members must possess the necessary technical know-how to carry out the project in order to successfully finish the research. We ensured that we could obtain the necessary expertise to finish the project in addition to the knowledge we already have.

2. Economic Feasibility

When we conduct the project, financial resources are crucial. We made sure we had enough money to finish the project without needing to make a midway halt. We also made careful to budget for future unanticipated expenses.

3. Legal Feasibility

When a project violates laws pertaining to social media, data privacy, or zoning, it does not fulfill legal feasibility. We ensured that our suggested system does not violate any laws.

4. Operational Feasibility

This has to do with how much of the project can be finished to satisfy the needs of the business. Members of the Underground Music Coven and I held a conversation to ensure our operational viability.

5. Scheduling Feasibility

The term "scheduling feasibility" refers to the ability of a project to be finished and delivered on time. It is one year in our situation. We ensured that the project will be completed within the allotted time frame.

Process of gathering secondary data for our research.

We engaged in a range of activities. These included researching current systems, consulting internet materials including articles and tutorials, and compiling data from books and publications. We carried out a feasibility analysis to ascertain the project's potential after finishing the requirement gathering stage. The feasibility study covered a number of important topics;

1. Starting with technical feasibility: We made sure that everyone in the team had the technical know-how needed to finish the project, and we also took the necessary actions to pick up new skills as needed.

2. Next, we assessed economic feasibility: realizing how important financial resources are to the project's success. We made sure we had enough money to finish the job, and we made backup plans in case we ran into financial difficulties.

3. In addition, we addressed legal feasibility: making certain that our suggested solution did not violate any applicable laws or rules, such as those concerning social media or data privacy.

4. We also considered operational feasibility: which refers to the ability of the project to meet the needs of the company. We are planning to work closely with the businesses such as schools in order to acquire more information regarding this area.

5. Finally, we evaluated scheduling feasibility: which relates to the project's ability to be completed and delivered within the defined time frame. Given that our project timeline was set at one year, we ensured that our proposed project could be delivered within this timeframe.

3.2 Analyzing

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

3.2.1 Functional Requirements

- To establish and preserve individualized user profiles, the system will gather and retain user data, such as learning preferences, historical performance, and preliminary evaluations.

- The system will employ a simple recommendation algorithm that evaluates user profiles and makes recommendations for pertinent educational materials according to each user's requirements and preferences.

- A real-time adjustment mechanism will be incorporated into the system to allow the recommendation engine to modify and update recommendations in response to user interactions and input.

- The recommendation algorithm will use a hybrid strategy to improve the precision and flexibility of recommended content by combining content-based and collaborative filtering techniques.

- By combining user choices, content tags, and recommendations, the system will put together dynamic learning pathways that provide each user with a unique learning experience that changes and evolves over time.

3.2.2 Non-Functional requirements

- The system must guarantee that user data is kept safe and only accessible by authorized personnel.
- It must be able to manage massive volumes of data and respond to user requests quickly and reliably.
- The system ought to have the flexibility to grow or shrink in response to shifting user needs and data volumes.

- There should be minimal downtime for maintenance or updates, and the system should always be dependable.
- Users of all technical levels should find the system straightforward to use and manage.

3.2.3 User requirements

1. It should be simple for users to set up and maintain their profiles, which include details about their learning preferences, objectives, and historical performance.

2. It should be possible for users to offer comments on suggested content, voicing their approval or making suggestions for enhancements.

3. When the system modifies its recommendations in real-time depending on user interactions and comments, users ought to be notified or updated.

4. By actively participating in the feedback loop and influencing future recommendations, learners can feel empowered to shape their learning experience.

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.

3.2.4 System requirements

Software requirements

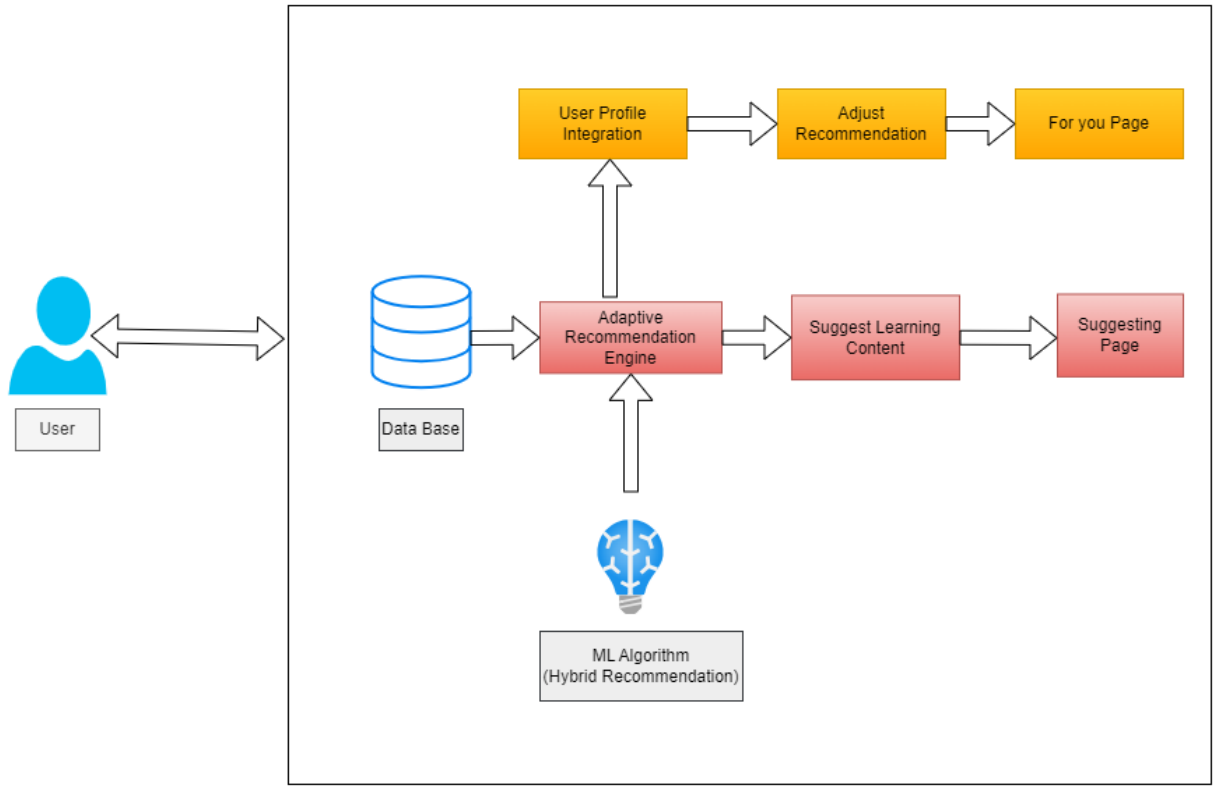
- Operating System: Windows
- Web browser: Google Chrome
- Database management system: MySQL
- Programming languages: Python, JavaScript, and PHP
- Frameworks: React, Django, and Node.js
- Development environments: PyCharm, PhpStorm, NumPy, pandas
- Version control system: Git
- Application programmable 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

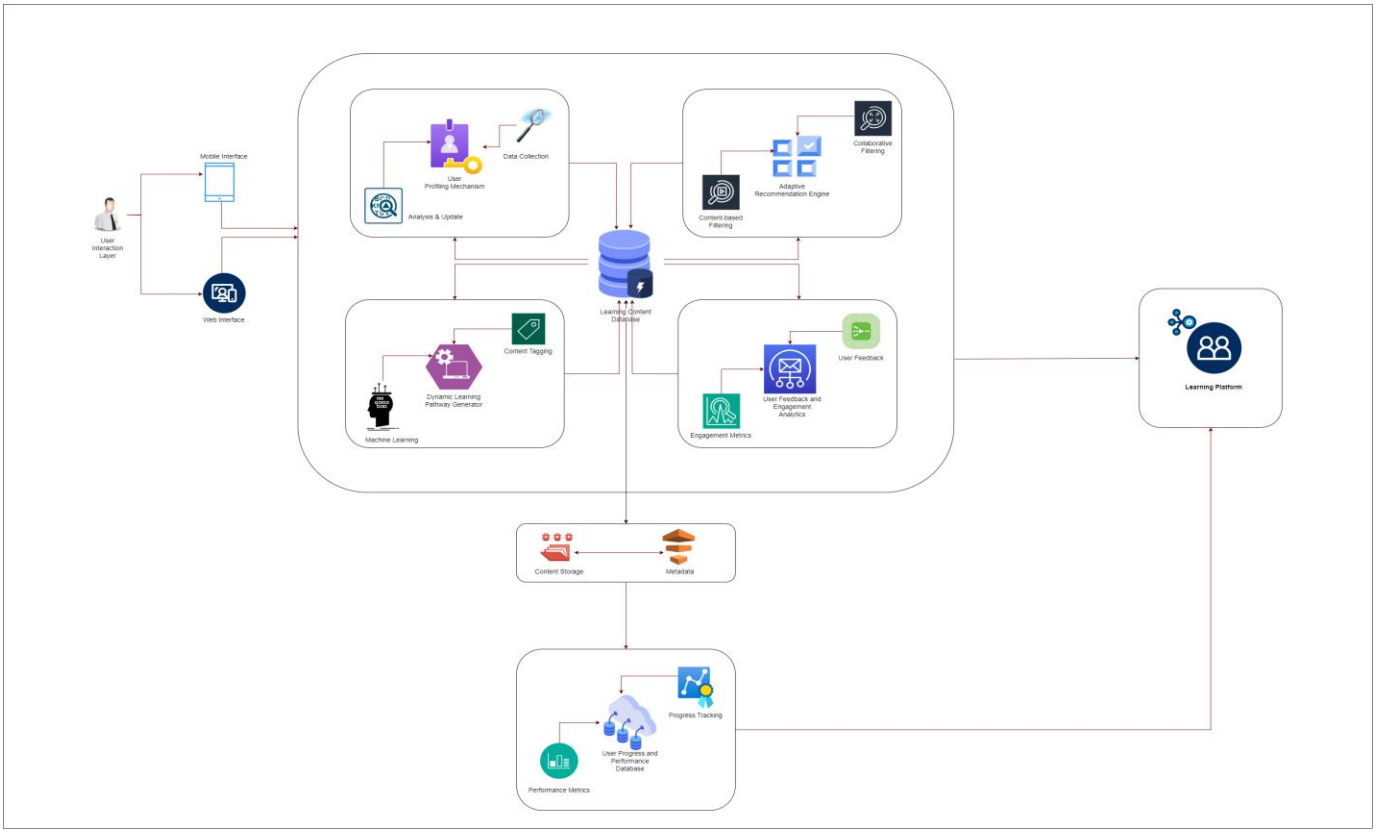
3.3 Design

In order to move on with the design stage, we have created a system architecture diagram that unifies all required parts. Using the Figma program, each web application interface will be wireframed to start the design step. After the wireframes are finished, usability tests will be carried out with high-fidelity prototypes, emphasizing the identification and resolution of problems from the viewpoint of the user. By lowering the possibility of user acceptability testing failing, this procedure will save time and effort prior to the implementation phase, making it both efficient and effective. After that, we will develop the database and attribute identification for the system, and then we will build the hardware and software solutions.



High level system architecture diagram f 1

Figure 2 : High level system architecture diagram for proposed component



High level system architecture diagram f 2

Figure 3 : High level system architecture diagram for the whole system

3.4 Implementation

All of the concepts created in the earlier phases are realized in this step. Any changes implemented at this point could have a significant impact. According to the Agile methodology, process modifications may lead to recurrence.
Our goal is to create four modules.

We develop four modules within the component;

1. User Profiling Component: This part compiles and examines user information to provide customized profiles. It takes into account variables like learning preferences, historical performance, preferred learning techniques, and any preliminary evaluations.

2. Adaptive Recommendation Engine: This central component makes recommendations for educational material based on the user's profile using a simple recommendation algorithm. In response to user interactions and comments, it modifies recommendations in real time.

3. Dynamic Learning Pathway Generator: This part arranges suggested content in a dynamic learning pathway for every user. It guarantees a diverse range of formats and levels of difficulty, fostering an all-encompassing educational experience.

4. Engagement Analytics and Feedback Loop: This In order to improve the system as a whole, this component tracks user involvement, examines learning patterns, and incorporates input. It helps with ongoing adaptation and development.

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

1. Define Objectives and Scope: To help with the implementation process, clearly identify the goals, target market, and Adaptive Recommendation Engine's scope.

2. User Profiling and Data Collection: Establish a strong user profiling system to gather information on prior performance, learning preferences, and preliminary evaluations. To generate individualized profiles, make use of data collection techniques such user interactions, feedback, and stated preferences..

3. Adaptive Recommendation Algorithm: To improve suggestion accuracy and personalization, create a hybrid recommendation system that combines content-based and collaborative filtering techniques.To continuously learn from and adjust to consumer preferences over time, employ machine learning models.
4. Dynamic Learning Pathway Generator: Create and put into use a dynamic learning pathway generator that takes user choices, learning objectives, and content tags into account. Make that the system has the ability to dynamically modify learning paths in response to changing user preferences and performance.

5. User Interface (UI) Design: Make the Adaptive Recommendation Engine's interface simple to use so that people may explore and communicate with it with ease. To improve the user experience overall, provide interactive components, dashboards that are easy to use, and clear images.

6. Model Creation and Training: Create machine learning models using the selected recommendation method as a basis. Utilizing past user data, train the models, then keep them updated to account for evolving user preferences.

7. Integration with Existing Systems: Assure smooth integration with the current educational technology infrastructure, learning management system (LMS), or e-learning platform. To facilitate data sharing between the Adaptive Recommendation Engine and other components, establish API connections.

8. Engagement Analytics and Feedback Loop: To monitor user interactions, completion rates, and other pertinent metrics, put in place an engagement analytics system. Provide a feedback loop so that users can offer suggestions for new content, enhancing the system's flexibility.

9. Testing: To find and fix any problems, carry out comprehensive testing, such as unit, integration, and user acceptance testing. To make sure the Adaptive Recommendation Engine is reliable and accurate, use a variety of datasets and real-world scenarios.

10. Deployment: For initial testing, deploy the Adaptive Recommendation Engine on a staging environment. Deploy the system to the production environment for real-time user interaction after it has been validated.

11. Monitoring and Maintenance: Use monitoring tools to keep tabs on user activity, system performance, and possible problems. Maintain and update the system on a regular basis, taking user feedback into account and improving the recommendation algorithms all the while.

3.5 Software Testing

The software testing phase, which comes after the implementation phase, is where flaws and problems that arise during program execution are found. In this step, every subcomponent must be extensively tested. There are two primary categories for the testing phase:

1. Functional Testing: Unit, integration, user acceptability, and component testing are all included in this. Both black box and white box testing methods ought to be applied in this case.

    a. Unit Testing: This kind of testing is done on every component to guarantee proper operation.

    b. Component Testing: Similar to unit testing, it involves assessing a component of software apart from the rest of the system.

    c. Integration Testing: This is to verify that, once the components are integrated, the application operates as intended.

    d. User Acceptance Testing: In this kind of functional testing, the end user confirms that the system satisfies their needs.

2. Non-Functional Testing: This includes security testing, usability testing, and performance testing.

    a. Performance Testing: In order to evaluate the system's performance, this monitors reaction times, locates bottlenecks, and pinpoints failure areas.

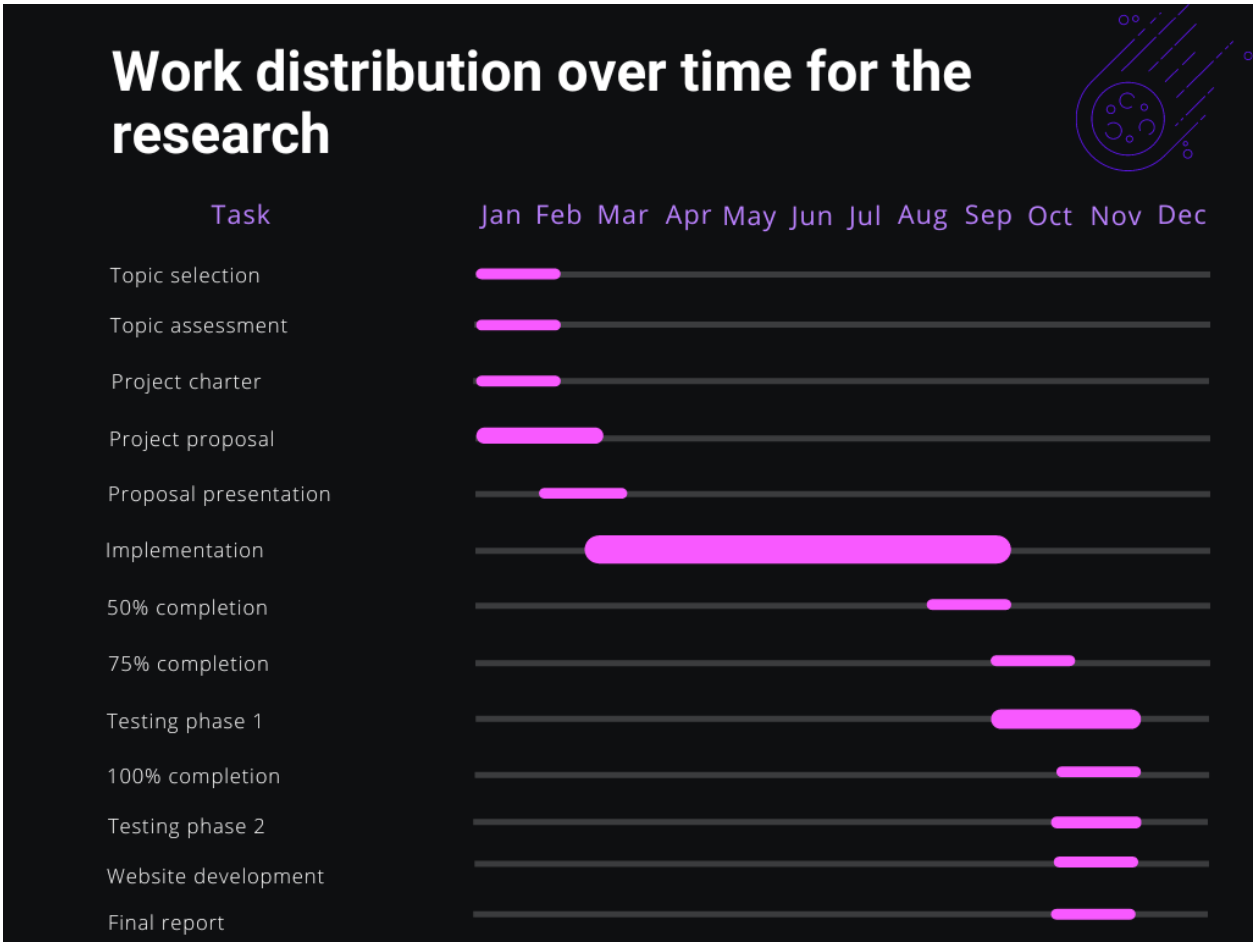
    b. Usability Testing: To ascertain whether the system's user experience is ideal, this is done in conjunction with end users.

    c. Security Testing: This looks for bugs in the software that could compromise data.

Both functional and non-functional testing are to be conducted simultaneously.

3.6 Maintenance

The end of testing is not the end of the software development process. After the program is developed and released, it needs to be regularly maintained. To keep the software performing at its best, updates should be made to fix bugs, performance problems, security flaws, and accuracy issues.



Gantt chart 4

Figure 4: Gantt chart

4. 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.

The planned personalized e-learning system will be commercialized using a planned and staged approach, with important components such as an adaptive recommendation engine, dynamic learning pathway generator, user profile mechanism, and engagement analytics system. In order to determine the target market, comprehend rivals, and ascertain the system's unique selling propositions, market research and analysis will first be carried out. To increase awareness, a thorough marketing plan will be developed that makes use of social media, internet platforms, and collaborations with academic institutions. Concurrently, a pilot program will be initiated to collect input from early adopters, allowing for iterative system improvement based on user experiences.

Scalable pricing options that accommodate individual users, educational institutions, and business clients will be created to enable wider adoption. Establishing strategic partnerships with providers of educational content will augment the diversity of learning resources that are accessible. It will be essential to continuously measure user happiness and participation in order to make updates and enhancements possible. We'll put in place efficient customer service and training initiatives to make sure users have a smooth onboarding process. The personalized e-learning system will be positioned as a market leader during the commercialization process, with a focus on its user-centric design, adaptability, and efficacy in improving the learning experience.

5 DESCRIPTION OF PERSONAL AND FACILITIES

Table 2

Member	Component	Task
Abeykoon R.M.S.P	Adaptive Recommendation Engine	Choose and implement a recommendation algorithm. Choose between content-based or collaborative filtering, or a hybrid strategy depending on the needs of the project. Selected algorithm to produce the first set of suggested learning content. Integrate the user profile into the recommendation algorithm. Make sure the user's preferences are taken into account by the recommendation system. Profile, which includes learning preferences, historical performance, and any traits found in the user profiling section. The recommendations are made more relevant by this integration.

		Develop a mechanism for real-time adjustment of recommendations Establish a system that keeps track of user interactions with suggested Content suggestions should be updated in real-time in response to user clicks, views, and other pertinent interactions to ensure that they are responsive to changing user preferences. Incorporate like/dislike buttons or other feedback mechanisms. Include tools that let users comment on content that is suggested. Gather and examine this feedback to gain a deeper understanding of user preferences and adjust the recommendation engine accordingly. Implement mechanisms to refine recommendations continually. Refine the recommendation system with user feedback and interaction data. Update the algorithm frequently to enhance suggestion accuracy and adjust for alterations in user behavior.

		Develop a system for dynamically updating recommended content. Make sure the recommendation engine has the ability to dynamically include new material or revisions to already-published material. This maintains the advice current and in line with the most recent resources available on platform. Implement performance monitoring tools. Include tools for tracking the recommendation engine's performance. Monitor measures like click-through rates, user happiness, and recommendation accuracy to determine how effective the recommendations are.

Table 2 : Description about personal and facilities

6 BUDGET AND JUSTIFICATION

Resource	Price (LKR)
Electricity	7000
Stationary	2000
Internet	7000
Server / domain	9000
Total	25000

Table 3 : Budget and budget justification

7 REFERENCE LIST

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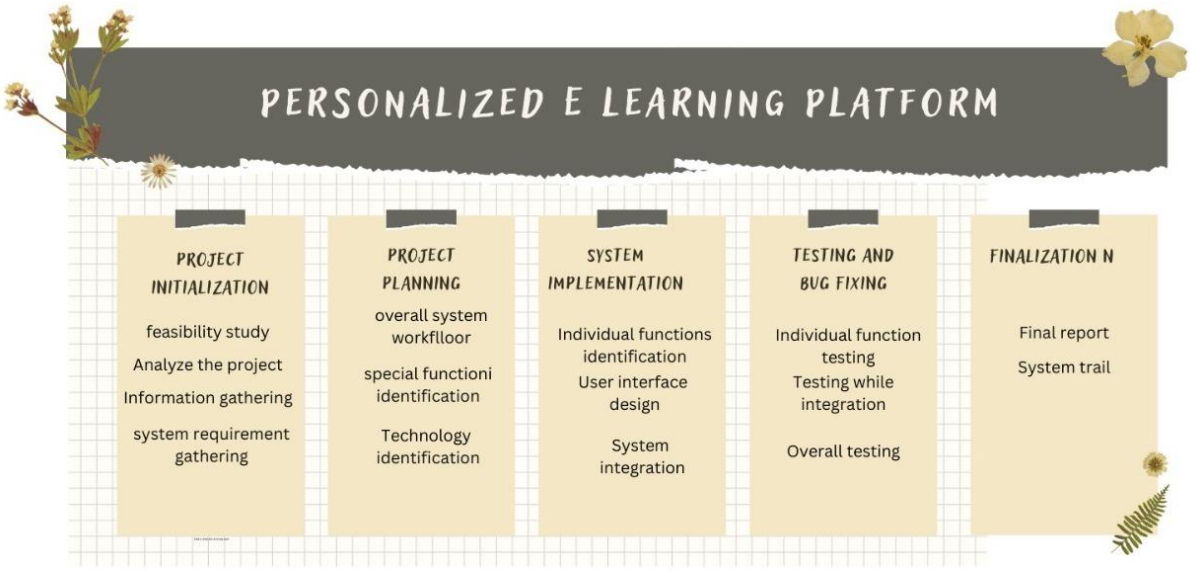
8 APPENDICES

Appendix: Work breakdown chart



WBC 5

Figure 5 : WBC