**“AITor” EDUCATION PLATFORM - A PERSONALIZED STUDENT PERFORMANCE ANALYZER AND RECOMMENDATION SYSTEM**

2022-017

Project Proposal Report

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Department of Information Technology

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# **DECLARATION**

We declare that this is our own work and this 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. The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

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| **STUDENT NAME** | **STUDENT NO.** | **Signature** |
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Signature of the supervisor Date

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# **ABSTRACT**

According to Rosenberg and Wentling, the term E-learning refers to the use of internet technologies that are capable of providing a wide range of solutions to enhance knowledge and performance[1]. Although the E-learning technologies were evolved over decades, with the outbreak of the Covid-19 virus, the demand for the E-learning technologies was suddenly increased, since most of the education institutes were migrated from traditional methods of education towards the E-learning technologies[2]. With that sudden emergence of the e-learning technologies, the quality, effectiveness, and productivity of the E-learning and E-learning platforms were highly questioned in the society.

Each student process their own learning style which defines how the learner acquires the knowledge effectively while learning[3]. Even in traditional classroom education, it is very hard to identify the personal learning styles of learners, which the lack of physical interaction in E-learning makes it much harder to achieve it in the E-Learning context[3]. But having the awareness of personal learning patterns will empower the learners as well as tutors by allowing them to make correct decisions throughout their education journey, to recommend the most suitable learning materials that cope with personal learning style, and to make accurate analytics and recommendations about individual’s education.

“AITor” is an assistive and personalized E-learning platform that is based on identifying the personal learning style of learners. With having the luxury of knowing the learning patterns of learners, “AITor” will be empowered with the features such as personalized and progress-based learning material recommendation, Personalized student performance analysis, personal performance-based skill prediction, career recommendation, learner classification and analyzing features. This system will be presented as a web-based E-Learning platform and will use raw video footage with student’s facial emotions, continuous assessments, and predefined questioners as inputs in predicting the learning pattern.

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## **INTRODUCTION**

## **Background**

Although the origin of the concept of E-Learning is believed to be in the 1980 s, it took around fourteen years to develop education platforms that was specially dedicated for E-Learning [4].As the first specialized education platform, a LMS, named “Cecil” was developed and launched in 1996[4]. With the introduction of “Cecil”, the concept of learning platforms was highly emerged and discussed among the globe and number of universities and education institutes were started to transfer to education platforms and learning management systems from their traditional learning content development and delivery methods. Although a considerable number of universities over the world are migrated as above, most universities of them were used their learning management systems only for learning content delivery and management rather than using them for fully digitizing their learning and teaching process. But, with the outbreak of the Covid-19 virus, since lockdown and social distancing has been taken as prevention measures spread of Covid-19, it was caused to shut down the conventional classroom education and hence most of these educational institutes had to move towards fully digitalized learning and teaching methodologies[2]. With that sudden transformation, the quality and productivity of fully digitalized E-Learning were highly discussed and due to the lack of technical maturity of the existing E-Learning platforms, most of their defects and drawbacks were highlighted.

A major drawback that was highly marked was the personalization problem of the existing E-Learning platforms. Not only in the E-Learning context, but even in the typical classroom education also, personalization was one of the major challenges since, in the conventional classroom education system, one teacher has to teach many students at the same time, and there, they use the same learning content, teaching technique and a same educational model for each student in the classroom[5]. This approach is widely known as the “one size fits all approach”. According to [5] and [3]each learner has their own learning style which defines how the learner acquires the knowledge effectively while learning. In 1991, Cooper and miller claims that the accordance between the teaching style with the learning style of a particular student relates towards the performance and progress of that student. Through the conventional classroom educational approach, it is very difficult for a teacher to figure out the most suitable learning pattern of a learner. Even a teacher was able to identify the personal learning style of a learner it is very hard to adjust his/her learning pattern according to each and every learner in the class[5]. In contrast to the classroom education, E-learning offers a flexibility to teach each individual student in a way that most personalized to their learning pattern since through a web application, since it is possible to provide verity of learning materials that fits for different types of learning styles and then recommend learners, the most appropriate learning materials that aligns with their learning style.

Also, it is clear that determining the learning style of each learner is playing a crucial role in this entire approach and the success of the entire process is based on the accuracy of the determined learning strategy. Although the learning style prediction plays a vital role in the approach, without recommending and providing the most suited learning materials that blend with the purposed learning style, it is unable to a personalized learning approach to be successful.

To study how the learning materials referred by students affect the performance of the students in an E-Learning platform, it was conducted a survey among university students of Sri Lanka that have participated 51 students, that are in more than five different reputed universities.

Before identifying the opinions about the relationship between learning materials and the student performance to get an idea about the sample used in survey and their experience in using E-Learning platforms, a general question was presented by questioning about their experience in using E-Learning platforms.

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Figure 1.1: Summery of responses about the question of, students experience in using E-Learning platforms

According to Figure 1.1, it can be stated that most of the university students in Sri Lanka at present are more familiar in using E-Learning platforms and the sample that was used in this survey has a better experience in the challenges, pros, cons, and other characteristics of the E-Learning platforms. Apart from that, the result that has gotten for this question concedes the amount of attention that the respective parties need to pay on developing, fine-tuning, and maintaining E-Learning platforms since it clearly shows that more than 98% of university students have migrated to E-Learning platforms, at least in a minimal extent, in their education.

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Figure 1.2:Response for the question about the relationship of learning experience and the characteristics of learning materials

The question depicted in figure 1.2 was introduced to the survey with the intention of gathering the opinions of university students about the relationship between the learner's personal learning pattern with the materials that they refer. Although it does not explicitly state the relationship of learning materials with learning style in the question, this question was able to fulfill the intention. Thus, as shown in figure 1.2, among all the responses that have got, only 4% believe that there is no relationship between their learning style and the materials that they are preferring. Thus, 96% percent of students either completely believe or do not have a clear idea of the relationship of their personal learning pattern with the referring materials.

The conclusion that can be derived from figure 1.2 shows a clear correlation with some of the literature that stated the relationship among learning materials with the personal learning style. These pieces of evidence provide a considerable amount of motivation to introduce personalization to learning platforms and on the other hand, it clearly depicts the importance of introducing a learning material recommendation system that embedded with a personalized E-Learning platform.

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Figure 1.3:Response for the question about the relationship of the results of exams and the characteristics of learning materials

The result of the question in Figure 1.3 further evinces the concluded inference of the question in Figure 1.2. More than 90% of the sample accept that the learning materials that they are referring, are directly related to the results that they are getting. Further, this result can introduce as evidence of the relationship of learning material with performance. As a conclusion, it can clearly claim that in a given sample of university students in Sri Lanka, more than nine-tenths of students believe that the materials they are referring, are affected with the results that they are getting in the exams.

Thus, by considering all of the above facts, it is clear, how it is important to consider the personalization aspect in developing education platforms and how it is important the personalize learning materials in considering the learner’s learning experience and their progress. Thus, the rest of the paper is predominantly based on different aspects of the learning material recommendation in E-Learning platforms.

## **Literature Survey**

According to the proposing assistive learning management system, learning material recommendation feature plays a vital role by directly effecting in controlling the progress and the effectiveness of a student through a given learning path. Making most accurate predictions will enable the students to learn the target subject area in a more understandable manner and in a memorable nature. Furthermore, material recommendation prominently affects with the student’s tendency towards a given subject area. The main intension of embedding a learning material recommendation feature into the purposed learning platform is to improve the progress and effectiveness of the students by recommending the learning materials that align with their learning pattern and the learning preferences.

As a result of gasping the explosive growth of IT into the field of education, there are many freely available and paid learning resources were developed and available over the internet. With that fact, it is challenging to choose the best suited learning materials that align with the needs of subject area and the personal preference[6]. These two challenges are known as personalization and information overloading and learning material recommendation systems are used in the context of education in order to overcome the mentioned challenges using a computer science approach[6].

Recommendation algorithms were widely used in the contexts of E-Commerce platforms, Entertainment systems, social media platforms to recommend items based on the user interactions with these systems. With respect to the used strategy, recommendation approaches can be categorized in to three categories[7].

1. Content-based recommendation
2. Collaborative Filtering (CF)
3. Hybrid Recommendation.

Beside the above three main recommendation approaches, Salehi considers Latent semantic analysis, Demographics and Data-mining techniques as other viable recommendation strategies and demonstrates a detailed comparison of all of these strategies and introduces some opinion about the feasibility of using them in learning material recommendation.

Content-based recommendation approaches takes the previous preferences of the user into account and recommend the items based on them. In contrast to Content-based recommendation, Collaborative Filtering groups the users that are having similar choices into similar groups and recommend items according to the preference of entire set[8].Although both content based and collaborative filtering techniques two powerful techniques that are used in most recommendation systems, they have their weaknesses and strengths as well. With having the intention of mitigating the drawbacks of both types of techniques while empowering with strengths of both techniques, hybrid recommendation approaches were proposed and they will use combination of two more recommendation techniques to produce highly accurate recommendations while improving the performance of recommendation algorithms[9].

In the discussion of learning material recommendation, it is not vice to only rely on the literature of similar learning material recommendation systems, hence there are very powerful and accurate recommendation techniques and algorithms are already using in other contexts such as E-Commerce. Thus, in the initial part of this literature review it will review some of common recommendation approaches and practices using appropriate research papers and then at the latter part this review will draw the attention towards more domain specific recommendation approaches based on some already purposed solutions.

Table

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Figure 1.4:Comparison of recommendation strategies [7]

Isinkaye, Folajimi and Ojokoh presents three major phases of each recommendation system called Information Collection Phase, Learning Phase and Prediction/Recommendation Phase. According to the researchers, gathering necessary information of the users to create the user profile or a model will be done in the Information Collection Phase. Most systems use explicit and implicit feedbacks in order to build and to finetune this model/profile. In the learning phase it uses learning algorithms to derive the features and preferences of users, based on the model/profile built on the Information Collection Phase. As the third and final phase, Prediction/Recommendation Phase, predicts the items that user may prefer. This prediction are done via the model made in first phase or through that data gathered by observing the user activities with the system[9].

Further, the above literature divides the collaborative filtering technique in-to two sub techniques called Memory based techniques and Model based techniques, based on the technique of categorizing users into different neighbor groups. Further it claims that Model based techniques improves the performance of collaborative filtering by using a pre-computed model which can be build using machine learning or data mining techniques. Finally they highlights learning algorithms such as Association Rule, Clustering, Decision Tree, Link Analysis, Regression and Bayesian Classifiers, as widely used algorithms in model based recommender systems[9].

In 2007 Feng-jung Liu and Bai-jiun Shih highlights, difficulty of learning resource sharing, High redundancy of learning materials, lack of course briefs as three major issues with E-learning courseware platforms and proposing a learning material recommendation system while having the intension of addressing these issues. There Feng-jung Liu and Bai-jiun Shih tries to approach the problem through two aspects. They are using LDAP (Lightweight Directory access protocol) and JXAB (Java Architecture of XML Binding) technologies, aiming to empower their recommendation system by solving the difficulties of content sharing using a network related approach. On the other hand, Association rule and Collaborative filtering techniques were used by utilizing their system by employing power of machine learning and data science. While association rule used for identifying the keywords that were used for searching the material and their relationship with those materials’ collaborative filtering was used to correctly filter the keywords of each course. Also it was used Apriori algorithms and Tree based algorithms as the association rule mining strategies for this recommendation system[10].

According to the solution purposed by Feng-jung Liu and Bai-jiun Shih in 2007 their final product was able to integrate with different LMS ‘s and they have designed a material registration interface to cater that facility. Thus finally they have introduced a learning activity based E-Learning material recommendation system which made up with four parts called data collecting and Indexing , Inquiring services , Association rule and collaborative filtering[10].

In 2008 Feng-jung, further develop his idea about “learning activity-based E-Learning material recommendation system” and took it forward up to a “Self-Directed E-Learning material recommendation system” by introducing an on-line Evaluation feature into it. Here, Feng-jung, converts his e-learning platform into an “Problem Based e-Learning” platform which recommend the learning materials based on the results getting by previously given test. This system presents a test to the learner, the system recommends the materials by analyzing the problems that the student got in answering to the given test. In considering the recommendation system, there was no much improvements made to it other than introducing a characteristic evaluation formula as a criterion for the rank of the recommendation[11]. There it recommends the materials by analyzing the activities of previous learners with the system. It keeps terms that learners used to search contents within the system and according to the frequency of the use of that term, it assumes that those are the keywords that are most appropriate keywords for a respective module/unit and then recommend the materials accordingly. Thus In 2012 Feng-jung was able to achieve the “Self-Directed E-Learning Concept” by adopting the problem based learning strategy into his literature[11].

In 2012 research team of three with Mojtaba Salehi introduces a novel approach by having the intention of contributing to the material recommendation in learning management systems by improving the quality and accuracy of recommending materials while addressing the problem of scarcity with the use of implicit attributes of learners and learning materials. This approach shows a clear advancement in learning material recommendation compared to research of Leu, since it considers both implicit and explicit types of attributes of both learners and the materials. Salehi and the team uses genetic algorithm for extracting implicit attributes of learner from historical rating in the shape of weight vectors. Then it will produce recommendations based on the produced weight vectors using a nearest neighbor algorithm[6].According to the Salehi and the team, they statically claims that their approach performs better than the tradition collaborative filtering based material recommendation approaches before.

## **Research Gap**

As it reviewed in the above literature survey the learning material recommendation feature for E-learning platforms were developed overtime and many researchers have been conducted their research by considering many facts that allows to improve the accuracy and efficiency of the recommendation. But in diving in to the deep of these research it can clearly figure out that almost all the researches that reviewed above [6]-[11], are basically done their researches with having the intention of improving the accuracy and the effectiveness of their material recommendation system rather than focusing on the progress of the learner with the recommended learning materials.

Nevertheless, by analyzing the survey conducted above and by referring to the paper[3], it can be easily argued that the progress that the learners are getting in their path of education is directly connected with the materials that they are used to study the relevant discipline. Thus, neglecting the learner progress in learning material recommendation systems can be identified as one of major drawbacks that exist with the learning management and learning material recommendation systems at present.

By analyzing the findings of the literature survey, it can clearly determine that research A [10] is based on addressing the difficulty of learning resource sharing, High redundancy of learning materials, lack, of course, briefs problems in traditional learning material recommendation systems through a combined approach which consist with both network-based technology and through collaborative filtering technique. Further, this research draws its attention to the learner's behavior with the recommender system, since this recommender system is developed as a search engine. Another remarkable infirmity that can identify in [10] is that its attention towards the characteristics of learning materials is very minimal.

However, it is clear that Liu is tried to mitigate some of the drawbacks that were in his previous approach through the second approach that was presented in 2008 as [11]. Thus, in research B [11], Liu introduces the “Problem-based learning” technique to the recommender system which is capable of recommending learning materials based on the problems getting while answering to a given test. Although this aspect can be introduced as a more learner-centric characteristic, still this research also suffers from the issue of less concern towards the learning material related attributes.

Also, another obstacle that finds in embedding research A or research B like approach into E-Learning platform that, they recommends the learning materials based on the course content that students are following, is both of them being search engines. By being a search engine that recommends learning materials, they are unable to cater to the course content-based requirements that are needed in recommending learning materials that are having the ability to clearly accent the course content. Therefore, the need for a recommendation approach that takes course content, learning material, and learner-based attribute into consideration has emerged.

Although Salehi and a research team introduce a prominent approach in learning material recommendation by emphasizing the importance of implicit and explicit attributes of both learners and learning materials in research C[6], the implicit attributes of materials that considered are limited to very few attributes such as historical ratings for the learning materials given by the students. Although the importance of considering learners’ implicit attributes is highly appreciated in the paper, there cannot find any significant contribution of these attributes in implementing its model using the proposed approach.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Case Study** | **Facts to consider in learning material recommendation** | | | | | |
|  | **Explicit Attributes** | | **Implicit Attributes** | | | |
|  | **Materials** | **Learner** | **Materials** | **Learner** | | |
|  |  |  |  | **Problem Based Learning** | **Knowledge Gaps** | **Learning Style** |
| Research A[10] | ü | ü | û | û | û | û |
| Research B[11] | ü | ü | û | ü | û | û |
| Research C[6] | ü | ü | ü | û | û | û |
| AITor | ü | ü | ü | ü | ü | ü |

Table 1.1: Comparison of research gap

As the definition suggests, AITor is a personalized E-Education platform that operates based on identifying the learning strategies and learning styles of learners and empowering learners in their learning process by supporting them with different needs according to the identified learning style. Thus, the learning material recommendation component addresses the personalization problem in existing learning material recommendation systems, by accommodating one of the major implicit attributes, “Learning Style” that defines the best way that learners grab the knowledge that is taught to them. Although many researchers have been tried to personalize the learning content delivery process through different approaches, as reviewed literature suggests in the above sections, the most prominent attribute that defines a measure of personalization in the education context is the learner’s personal learning style. As clearly depicts in the above research gap comparison table AITor is the only solution that tries to fill this gap by identifying and recommending learning content based on the learner’s personal learning style.

AITor addresses another research gap that allows improving the productivity of the learning and teaching process through supporting learners to progress in their learning process by recommending learning materials by identifying and analyzing their weak areas and knowledge gaps.

## **Research Problem**

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Figure 1.5:learner's opinion about the sufficiency of learning materials

According to the closed survey conducted, more than 70% of the sample directly or indirectly claim that the materials that they are getting from their universities and the lectures are not sufficient for studying a given discipline. This result can be introduced as one of the major reasons for going to additional learning resources for gathering the knowledge that they missed in the provided learning materials. Further, the survey conducted in [12]reveals that 52% of their sample uses YouTube for academic learning, 48% for information seeking. [12] further elaborates their result by dividing their result according to the exact purpose in using YouTube in their education and finally they were able to be revealed that collectively 71% of their sample used YouTube to learn about the course content that they are involved in.

Table

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Figure 1.6:Purposes of using YouTube for academic learning [12]

By referring to the above facts, it can clearly identify that a considerable portion of students in the present education stream tends to use different supporting E-Learning materials to grab the knowledge in different stages in their learning processes as well as especially in learning the course contents that they are involved in. But, at present most of the learners use traditional search engines in searching these materials. In this approach, multi-purpose commercial search engines provide the results without considering any proficiencies of either learners or the course content that they have been involved in. As Abdullah and Rahman[13] emphasize this is one of the major drawbacks that occurs in using multi-purpose commercial search engines in educational content searching. As depicted in [14] learners have their own learning styles and the most suited learning materials will differ with these personal learning styles of users. Thus, a level of personalization is needed to be introduced in recommending learning materials in modern E-Learning platforms and there cannot find a considerable contribution in order to successfully address this problem by considering learner specific implicit attributes such as learner’s strengths, weaknesses, knowledge gaps and especially the learning style.

Also, in considering the learning material recommendation system that has been proposed and implemented so far, a major weakness that can identify is, most of them were more focused on the technology and the approach they are using rather than learner-centric issues such as the progress of learner [5]. AITor is a solution that is designed by aiming to improve the performance of learners by addressing the personalization issue in modern E-Learning platforms by focusing on most of the learner’s implicit attributes such as knowledge gaps and the learning style.

# **OBJECTIVES**

## **2.1 Main Objectives**

According to the literature revived in above sections of the document, learners show a level of personalization in gasping the knowledge in education. This personalization can be explained as a implicit attribute of the learner called “Learning Style”. The main objective of AITor is to support the learning and the teaching processes of in education through a digital E-Education platform which enables learners to strengthen their learning process based on their personal characteristics and qualities while allowing tutors and other support parties of education to get detailed analysis of the learners in many aspects.

Another weakness that was found during the literature survey was, the lack of awareness of the learners about their strengths and weaknesses in education. Due to this reason, considerable amount students take erroneous decisions throughout their lives on occasions such as choosing correct learning paths, selecting carriers, etc. A state of former Commissioner of Examinations in Sri Lanka, Sanath Pujitha can be introduce as a one of best evidences that confirms the above fact. As he claims, around 80,000 students who sit for the GCE Advanced Level examination annually fail the examination due to the wrong selection of subject stream[15]. The analyzer part of the AITor was introduced with having the intention of addressing this issue by achieving one of its main objectives to provide detailed analysis of each learner based on their personal characteristics such as strengths, weaknesses and learning styles by allowing them to make better decisions is crucial occasions of their lives.

Accordingly, the main objective of the AITor, can be summarized as, to develop an all-in-one solution that introduces a personalized experience into the traditional education system while providing detailed analysis on student education based on their Learning Patterns. In achieving the main objective it is intended to achieve four main sub-objectives and they can be introduced as follows.

## **2.2 Specific Objectives**

### **Identification and prediction of best learning strategy**

This will be the first objective of the proposing learning platform. The identification of the level of personalization will be happen through this objective. In achieving this objective. A separate software component will be implemented that is embedded into the main platform. Through this component, the system will predict the best learning strategy of the student.in achieving this objective a supervised ML model will used which get data by iteratively performing pre-defined tasks. This module will continuously evaluate the student by allowing students to take part in different tasks assigned by the system. It is intended to use different resources in order to cover the subject area. These resources can be classified as text with theory concepts, visual explanations of the theory concepts (images/videos), verbal/audio books which contains theory concepts, Live lectures, and real-time engagement activities (solve a math problem with a bot). As the final output it will be able to suggest a single methodology or hybrid/ combination of several learning strategies to teach the student.

### **Identification and recommendation of learning materials**

The intention of this objective is to provide supportive learning materials to the learners by considering implicit and explicit factors of both learners and learning materials. The facts that will consider would be, learning content, learning style, and learner’s knowledge gaps. In achieving this objective, the authors have to deal with the two types of stakeholders, they are learners and tutors. In achieving this objective the authors have to consume the learning style that is predicted as a result of the sub-objective in section 2.2.2 and build up a hypothesis to categorize the learning materials based on the receiving style. Thus, this recommendation should happen according to the characteristic of both learners and the learning content.

Further, in fulfilling this objective, authors have to implement a mechanism to integrate with different resources that are providing learning materials (Third-party learning platforms). Thus, here, authors have to consider the feasibility of integrating third-party learning platforms into the proposing solution and to decide the third-party platforms that are integrating with the system.

Another important fact that will be important in this objective would be the ability to decide learning content using the syllabus briefs that the tutors provide to the system. According to the proposing system, the tutors have the ability to feed the syllabus briefs and their materials into the system, and then the system should be able to extract the learning content using these materials and suggest the learning materials accordingly. Also In fulfilling this requirement, the authors have to do ample research and build up a hypothesis to extract the learning content using provided materials.

By considering these requirements, this objective can be divided further into three sub-objectives as follows.

* Building up a learning material classification approach based on their implicit and explicit attributes.​
* Building up an approach to identify learning content using syllabus briefs.
* Building up a learner classification approach based on their learning patterns, learning strategies, and knowledge gaps.

Other than the above main requirements, there should be given a way to accomplish the above requirements through the AITor web application. There, the authors have to deal with best practices of software development in order to expose these features through web application.

### **Performance analysis and personal skills Identification**

As experts specify, one of the major disadvantages in the context of E-Learning is the lack of relationship between the learners and teachers. Due to this reason, compared to the traditional classroom education, E-Learning makes it harder to identify hidden qualities of learners. This obstacle exists in identifying both technical skills as well as soft skills of the learners. The most common approach that most institutes and platforms used to measure the technical skills of learners is, the assessments. In referring to the literature, there cannot be find any considerable contribution that have happen in in E-Learning context in identifying soft skills of the learners. This objective is introduced in to the AITor with having the intention of addressing this issue through implementing a hypothesis that can identify both technical and non-technical skills of users in an E-Learning environment.

Here, Time management, confidence levels, and difficulty levels of questions in assessments like attributes will consider in measuring the technical skills of the learners. Most importantly, through fulfilling this objective, the proposing solution will be able to provide adequate insights into the soft skills of learners such as their analytical skills, problem-solving skills, creating skills, and learning speed.

### **Career recommendation and progress forecasting**

This is one of the major objectives of the proposing solution which exposes the collective output of all of the other objectives. The “Performance analyzer” part of the main objective will be done through this objective and learners, tutors, as well as higher management of institutes and even the industry people, will be benefitted from the result of this objective. Since the proposing solution closely deals with many of the hidden attributes of learners, all of these hidden attributes will be analyzed and finally, it will provide reports of different levels which is beneficial for different parties.

Further in this objective, the authors have to build up a hypothesis that analyzes the career opportunities by integrating with the available web recourses and finally implement a mechanism to recommend the best-suited careers by considering aspects of both learner and the industry.

# **METHODOLOGY**

## **Introduction and Basic User-Flow**

AITor, the proposing learning platform will expose all of its features through a web application that has embedded all the out-of-box features into it. Two types of basic stakeholders that directly interact with the system are identified and they are the tutors and students. As an intelligent web application, AITor provides different access levels for these categories of users by allowing them to take advantage of implemented features according to their intensions and according to their user roles. Another important user role would be third party stakeholders that are in the education system and they will be use the reporting features that are provided through the career recommendation and forecasting component.

According to the objectives that are intended to achieve through the case study, the entire AITor software application will consist of four major sub software modules that are responsible for accomplishing each of the above-mentioned objectives. These components can be listed as follows.

* Learning pattern identification component
* Learning material identification and recommendation component
* Student performance analyzer component
* Career recommendation and forecasting component

At the initial stage, AITor will consider and developed based on the computer science discipline and provide its features by aiming at the learners that are learning in the computer science stream. This section will provide a basic introduction about the intended methodologies that will be used in developing the learning material recommendation component of the application.

In implementing the learning material recommendation component of the AITor, three main aspects need to be taken into the consideration. They are,

* Identifying the subject scope using syllabus briefs provided by tutors.
* Identify and classify learning materials based on the content and their quality.
* Recommend learners with mostly matching learning materials that aligns with their learning style.

To accomplish the above-mentioned tasks, the learning material recommendation component will consist of four sub-modules that are responsible for achieving each of these objectives. These components can be listed as follows.

* Material classification module
* Subject Scope classification module
* Learner classification module
* Multidimensional attribute-based learning material recommender module

Diagram

Description automatically generated

Figure 3.1: Learning material recommendation module system overview diagram

The process of learning material recommendation will be initiated with the subject scope classification module. This module will provide a web interface to the tutors to upload their syllabus briefs and other related materials into the system. Through the provided syllabus briefs, the module will grab the core learning objectives and core contents to be taught. These results will provide through an API to the material classification module in order to classify the learning materials according to the identified learning scope.

By using the identified learning scope, the material classification module will classify the learning materials according to that scope. In acquiring learning materials, this component will expose to third-party web API s that allow to access their materials over APIs. The learning material classification will be happening based on the data that have been gathered through these APIs. In classifying learning materials, based on the learning styles of the learners, mainly three types of materials are considered and these three material types are video materials, audio materials, and text-based materials.

Learner classification will deal with a number of outside resources that are external to the material recommendation module and also collaborate with the material classification module that is inside the learning material recommendation module. The main external module that this module will interact with is the learner profile optimizer module.

## **Learner Profile Optimizer**

This will be a shared component in the AITor that is shared among all the sub-components of the entire solution. Collaborative filtering and association rule-based machine learning approaches will be taken to classify learners according to their personalized attributes and accordingly users will be profiled based on these factors. All of these profiling and learner classifications will be done through this component and with maturing the models, these profiles will be further finetuned and optimized. Accordingly these profiles will further personalized and all of other components will support this further optimization of these profiles and all the other components will use this learner profile optimizer to extract the learner specific characteristics in their use.

In identifying the learner’s learning style, the learning style identification module will go through two stages, named pre-evaluation stage and post-evaluation stage. The learning material recommender module also will have two stages parallel to these stages.

In parallel to the pre-evaluation stage of the learning style identification module, the learning material recommendation component will recommend the learning materials only taking the learning style of the learner as a learner-based implicit attribute in learning material recommendation. With the learner is progressing with their learning process, the student performance analyzer module will further analyze the student and accordingly, the learner profile optimizer will be further optimized. With this evolvement of the learner profile optimizer, as the second stage of learning style identification, the post-evaluation stage will be started. In this stage, the learning material recommendation module will take the advantage of the advancement of learner profile optimizer, and accordingly it will consider other learners specific characteristics such as their knowledge gaps and optimized learning style.

Multidimensional attribute-based learning material recommender will not be a separate module and it will behave as a module that aids to integrate the material classification module and learner classification module. By considering all the attributes that are processed by the above two modules, this module will match the best-suited learning materials with learner’s attributes and will expose the recommendations through an API.

## **System Architecture**

**Graphical user interface, application

Description automatically generated**

Figure 3.2: Overview System Architecture Diagram

* 1. **Proposed Technologies**

As it was explained in the previous section, according to the level of maturity of the users with the system, the system will use two stages in identifying the learning style and in recommending the learning materials. Thus, in the pre-evaluation stage of the learning style identification, the material recommender module will be completely based on the weights that have been provided by the learning style identification module, and accordingly, it will recommend the learning materials.

But with time, with learners maturing with the system, the learner profile optimizer will receive more learner-specific characteristics such as their weaknesses, strengths, knowledge gaps, and data about their progress. In this stage, the learner classification module will actively classify the learners by considering optimized learning style and the above-mentioned attributes. As [8],[9],[10],[11] emphasized, most of their authors were tried to use hybrid approaches rather than relying on either content-based filtering or collaborative filtering techniques independently. As they justify, this approach is much prominent in contrast to native approaches, since they provide the capabilities of both content-based filterings of collaborative filtering into the hybrid approaches. Thus, it was intended to use versions of PrifixSpan and Apriori algorithms in identifying patterns of the knowledge gaps and weaknesses of learners in classifying learners for the material recommendation.

The learning scope identification module will use to analyze the syllabus briefs that are provided by the tutors and extract the content of it and to derive the explicit attributes that are needed for the material classification component to classify the learning materials according to the subject scope. In implementing this component a combination of keyword extraction and sentiment analysis techniques were intended to be used and, since learning scope classification is not the main concern of the entire material recommendation component, it was proposed to use third-party service providers such as Google autoML sentiment analysis and their output will be further fine-tuned and further processed as necessary.

* 1. **Requirement Gathering**

In considering the requirement gathering in implementing the learning material recommendation components, it is identified two major aspects that are most crucial to consider. They are,

* What types of learning materials to be considered in recommendations (Ex: Audio, Video, Text, or other).
* What are the third party education platforms to be integrated in order to get the learning materials.

The requirement gathering phase of the learning material recommendation component will mainly be considering the ways of gathering user requirements to decide the above-mentioned facts.

Since at the initial stage the solution will develop based on the learners who are in computer science related disciplines, it was decided to conduct some closed surveys to gather their opinions about the above mentions facts and to grab the other related requirements from them. The requirement gathering surveys will basically aim at two types of users in the education field. They are,

* University students are in computer science stream.
* Academic staffs of universities in computer science stream.

Through the academic staff, it is going to collect their opinions about the most suited learning materials providing platforms that are more suitable for integrating with the proposing solution.

Other than the requirements that are gathered from the closed surveys that are conducted by the AITor authors, in requirement gathering, it will consider the results of the researchers that have done research, all over the world in the same domain. Thus, it was proposed to get participate the users as much as possible in the requirement gathering surveys and make more accurate decisions in finalizing the requirements.

* 1. **Feasibility Study**
     1. **Technical Feasibility**

As identified in the previous sections, since the learning material recommendation module will perform three major types of tasks in supporting overall learning material recommendation, in implementation of all of the above sub-modules respective machine learning techniques and technologies will be used. Thus classifying learners according to their implicit and explicit attributes will be done through hybrid filtering based machine learning algorithms such as Apriori and PrefixSpan. For the learning scope identification, it was decided to use well established third party natural language processing tools and some proven keyword extraction and sentiment analyses methodologies.

But rather than applying the above techniques directly into the solution, these algorithms will be slightly modified and reconfigured according to the necessities of the case study. Since these techniques and technologies are well established and have proven their abilities, using these approaches can ensure the technical feasibility of implementing the solution.

* + 1. **Implementation Feasibility**

It was intended to use best practices in software development throughout the development cycle of the entire solution. Thus, it was decided to follow agile methodologies in development and with a well-planned structure of the agile methodologies, each and every task will be well organized and planned upfront. Since the “Accepting the change” nature of agile methodologies, the authors are willing to face different challenges that are getting in the development and respond to the change. Thus, by considering the highly systematic approaches that are going to take in development it can claim that the proposing task can be implementation wise achievable.

## **PROJECT REQUIREMENTS**

## **Functional Requirements**

According to the objectives that are going to be achieved through this case study, the main requirement of the AITor platform would be, Implement an all-in-one solution that introduces a personalized experience into the traditional education system while providing detailed analysis on student education based on their Learning Patterns. Thus each sub-component has a set of requirements that need to be fulfilled in fulfilling the main requirement. Accordingly, the learning material recommendation component will support in achieving the main functional requirement through fulfilling four other requirements that are specific to personalized learning material recommendation. These four basic requirements of the learning material recommendation component can be listed as follows.

* Identify subject scope using syllabus briefs
* Recommend learning materials that aligns with learners learning strategy
* Recommend learning materials based on learners' weak areas
* Implement a platform which learners can access all learning materials through one place

## **Non-Functional Requirements**

By considering the patterns and trends of the users of using E-Education platforms that are already implemented, it was decided to consider three main non-functional requirements in the proposing solution. Thus,

* Availability
* Scalability
* Accuracy of recommendation

will consider as three major functional requirements for the proposing system. Since nowadays the means of education is vastly transformed towards the E-Learning means rather than classroom education, learners are spending more time in E-Learning platforms. Thus, the availability of the system and its features would be a crucial concern.

Since the transformation of traditional learning into E-Learning is actively happening at present, most learners, tutors and institutes are still migrating towards the E-Education platforms like AITor. Thus, the solution should be scalable with the increasing number of stakeholders and the resources.

The accuracy of learning material recommendations, is a one of important non-functional requirement for AITor, since it provides learning materials based on the personalized qualities of learners. Thus these material recommendations should highly align with the learners learning styles and should allow learners to progress by referring to these materials by making much accurate recommendations.

# **BUDGET AND BUDGET JUSTIFICCATION**

The budget that are needed for the entire AITor platform, can be classified into two categories. These categories will represent the cloud based cost that needed for development ad deployment and the other category represent the marketing cost for commercialize and market the AITor product.

## **Cloud Based Cost**

|  |  |  |  |
| --- | --- | --- | --- |
| Service | Monthly | First 12 months total | Currency |
| AWS Fargate | 36.04 | 432.48 | USD |
| S3 Standard | 1.16 | 13.92 | USD |
| Data Transfer | 0 | 0 | USD |
| Amazon Simple Queue Service (SQS) | 0 | 0 | USD |
| Amazon Elastic Container Registry | 0.5 | 6 | USD |
| Amazon EC2 | 43.87 | 526.44 | USD |
| Amazon Keyspace | 2 | 64 | USD |
| Other | 20 | 240 | USD |
|  |  |  |  |
| Cost | 103.57 | 1282.84 | USD |

Table 6.1: Cloud based cost justification

In the cost calculation, it is assumed that 100 users are using the system. Since the entire system will be fully hosted in AWS cloud and will uses different cloud features, the considerable portion of the cost will allocated acquiring cloud services. The “Other” category mentioned in the above table includes the costs for third party APIs that are used in getting learning materials in to the system.

## **Marketing Cost**

|  |  |  |
| --- | --- | --- |
| Marketing strategy | Monthly | Currency |
| Product branding | 50 | USD |
| Content branding | 20 | USD |
| Email and newsletters | 20 | USD |
|  |  |  |
| Cost | 90 | USD |

Table 5.2:Marketing Cost Justification

Since product commercialization is a considerable fact in considering the entire system, it will take considerable cost to the marketing related activities.

## **GANTT CHART**

**Chart, waterfall chart

Description automatically generated**

Table 7.1: Gantt Chart

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