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

2022-017

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Sri Lanka Institute 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**

With the COVID-19 virus epidemic, most educational institutes shifted from traditional ways of education to E-learning technologies[2]. With the quick rise of e-learning technology, society has questioned its quality, effectiveness, and productivity. As prior studies show, each student has a unique learning style that determines how well they learn[3]. Even in regular classroom education, identifying learners' specific learning styles is difficult. The lack of physical connection in e-learning makes it harder[3]. Discovering personal learning patterns empowers both learners and tutors to make proper decisions throughout their education journey, offer the most suited learning materials, and make accurate analytics and recommendations on an individual's education. "AITor" is a tailored E-learning platform that identifies learners' learning styles and provides a personalized learning experience for every learner. "AITor" will provide personalized and progress-based learning material recommendations, personalized student performance analysis, personal performance-based skill projections, career recommendations, learner classifications, and analytical features. This web-based E-Learning platform will use learner preferences, constant assessment progress, and questions that have already been set up to predict how people will learn.

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## **INTRODUCTION**

## **Background**

The idea of e-learning is thought to have first surfaced in the 1980s, it took about 14 years to establish specialized education platforms for e-learning [4]. A learning management system (LMS) called "Cecil" was created and released in 1996 as the first specialist education platform[4]. With the release of "Cecil", the idea of learning platforms became widely known and discussed around the world, and many universities and educational institutions began to switch from their conventional methods of developing and delivering learning content to educational platforms and learning management systems. Although many institutions throughout the world have made the aforementioned migration, most of them have simply used their learning management systems to provide and manage learning content rather than to fully digitize their teaching and learning processes. However, the COVID-19 virus outbreak forced a suspension of traditional classroom instruction because lockdown and social seclusion were implemented as preventative measures against its spread. As a result, the majority of these educational institutions were forced to switch to fully digitalized teaching and learning methods[2]. Due to the lack of technical maturity of the current E-Learning platforms, the majority of their flaws and shortcomings were revealed. The quality and productivity of fully digitalized e-learning were heavily contested as a result of that abrupt transition.

The existing E-Learning platforms' pronounced personalization issue was a significant negative. Personalization was one of the biggest challenges, not just in the context of e-learning but also in traditional classroom instruction, where one teacher is responsible for instructing multiple students at once while using the same educational model, teaching method, and learning content for all of them[5]. This strategy is frequently referred to as the "one size fits all approach." Each learner has a unique learning style, which, in accordance with [5] and [3], determines how the learner effectively gains knowledge during learning. Cooper and Miller asserted in 1991 that a student's performance and progress are influenced by the alignment of the teacher's approach with the student's preferred method of learning. It is quite challenging for a teacher to determine a student's best learning style using the traditional classroom teaching methods. Even when a teacher is able to recognize a student's unique learning preferences, it can be challenging to modify one's own learning style to suit all of the students in a class[5]. Through a web application, it is possible to provide a variety of learning materials that fit for different types of learning styles and then recommend to learners with the most appropriate learning materials that align with their learning style. In contrast to classroom education, e-learning offers the flexibility to teach each individual student in a way that most personalized to their learning pattern.

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 0:1.1: 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 with using E-Learning platforms, and the sample that was used in this survey has better experience of the challenges, pros, cons, and other characteristics of the E-Learning platforms. Additionally, the outcome of this question confirms the importance of developing, optimizing, and maintaining E-Learning platforms for the respective parties because it is abundantly clear that more than 98% of university students have switched to these platforms, at least to some degree, for their education.

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Figure 1.0:2:Response for the question about the relationship of learning experience and the characteristics of learning materials

With the goal of understanding more about the connections between learners' individual learning styles and the reference materials they use, the question shown in figure 1.2 was included to the survey. Although the question does not specifically indicate the connection between learning materials and learning style, it was able to fulfill the intention. Thus, just 4% of respondents, as shown in figure 1.2, think there is no correlation between their preferred learning method and the resources they use. As a result, collectively 96% of students have a vague understanding of how their individual learning styles and the referring materials relate to one another.

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 1.0:3:Response for the question about the relationship of the results of exams and the characteristics of learning materials

The answer to the query in Figure 1.3 further supports the implication drawn from the query in Figure 1.2. More than 90% of the sample agree that the learning resources to which they are turning have a direct bearing on the outcomes they are experiencing. This outcome can also serve as proof of the connection between learning content and performance. As a conclusion, it is evident that among a sample of university students in Sri Lanka, more than 90% of students think that the materials they are using have an impact on the exam results they receive.

Taking into account all of the aforementioned information, it introduces two crucial factors to take into account while developing e-learning systems. First of all, it emphasizes the significance of taking the personalization factor into account while creating educational platforms. It also highlights the relationship between learners' progress, their personal learning experience, and tailored learning resources. Because of this, the remainder of the study focuses mostly on various elements of the recommendation of learning materials in E-Learning systems.

## **Literature Survey**

The proposed assistive learning management system claims that the learning material recommendation feature plays a crucial role by directly influencing the management of a student's progress and effectiveness through a specific learning path. Making the most accurate forecasts would assist students in learning the intended material in a more understandable and memorable manner. Furthermore, the student's propensity for a particular topic area is strongly influenced by material recommendations. The major goal of integrating a learning material recommendation function into the intended learning platform is to increase students' progress and effectiveness by suggesting learning resources that are in line with their learning style and preferences.

As a result of the fast growth of IT in the field of education, there are a wide range of free and paid learning resources designed and available online. Because of this, it might be difficult to select the learning materials that are best suited to both your needs and the demands of the subject matter[6]. Personalization and information overload are these two difficulties, and learning material recommendation systems are utilized in the context of education to address them 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 1.0:4: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.

Table 1.1: Comparison of research gap

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **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 |

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 1.0:5: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.

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Figure 1.0:6: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

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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.

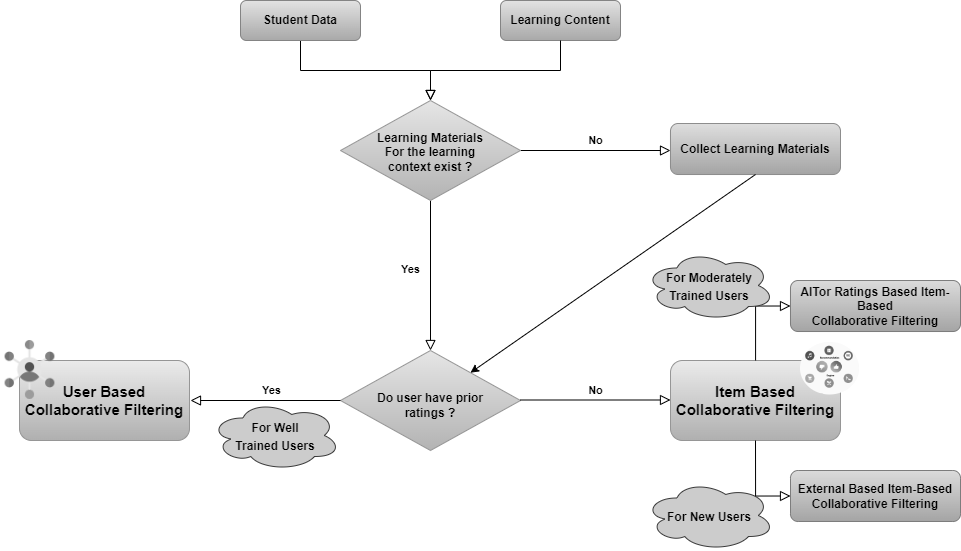
The initial part of the learning material recommendation component devotes itself to identifying the key learning areas of a given learning context. This process uses module outlines of different learning contexts as the input source for identifying the key learning areas of the given learning context. In the implementation, this employs a deep learning-based information extraction model to extract key learning areas from the module outlines. The predicted ”key learning areas” of this step will be fed into the learning material recommendation model as one of its inputs, which enables the learning material recommendation model to make recommendations specific to identified key learning areas. There are three major types of approaches that have been widely used and have demonstrated success in implementing recommendations in the context of recommendation systems.[5] They are,

* Content-based approach.
* Collaborative filtering approach.
* Hybrid approach.

The content-based approaches operate on the basis of information retrieval and machine learning. This model considers the similarity between different items and makes recommendations by comparing the items that users have accessed recently with other items. With compared to the content based approaches, collaborative filtering techniques mostly employees the personal characteristics on users. Between above two approaches, collaborative filtering presents more tendency towards the personalizing aspects since it depends on identifying similar users with respect to a common context.

The primary intention of this part of the study was to improve the productivity of the learning and teaching process. This was supposed to be achieved through personalized learning materials based on not only the attributes of learners but also considering the attributes of learning contents of the learning materials which are recommended and the syllabus contents which are specific to different courses. For the implementation, collaborative filtering-based approaches were chosen to align with the main goal of the research.

Although the research focuses on personalization, in the considered scope also uncovers content-specific characteristics. This demand shows that a content-based filtering technique is needed in this work. In a system that recommends coursework materials, it’s not enough to include human preferences to create accurate suggestions; it must also use coursework-related data to make more effective recommendations. Considering the aforementioned, it was decided to employ a hybrid recommendation technique that combines content-based and individualized criteria.



3:2: Learning Material Recommendation Method Selection Flow Chart

To introduce the context-specificity for learning material recommendations, it uses datasets constructed in a context specific manner. Prepossessing stages of data are made responsible for extracting the context-specific data and feeding refined data into the recommendation algorithm. Based on the above argument, the solution is made up of a combination of two major components as follows.

* Learning context identification component.
* Personalized learning material recommendation component.

The main responsibility of the learning context identification component is to identify the learning content and scope, based on the module outlines. The results of this component will be fed into the learning material recommendation component while being one of its main inputs. Due to preserve a high accuracy of this first step, it was introduced a mixed model which combined with a machine learning algorithm and a level of human interaction in identifying learning context. As the machine learning method, it was used deep learning based specific information extraction methodologies to extract the learning contexts by the module outline text document. This step was a combination of another three sub steps which the first one of it is used for parts of speech tagging. Through the first sub step it builds up trees which are represents the relationships between noun phrases and the remaining parts of the sentences. Through this step it was narrowed down the unstructured text data set in to list of phrases that can denote a set of candidate topics in the intended learning context.

## **System Architecture**

**Graphical user interface, application

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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.

# **IMPLEMENTATION AND TESTING**

## **Implementation of the Model**

Text

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Figure 4:1: Implementation of Data Preprocessor

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Figure 4:2: User Based Collaborative Filtering Implementation Using Cosine Similarity

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Figure 4:3 : Item Based Collaborative Filtering Implementation

## **Testing**

As the final stage of entire development of the “AITor” platform set of testes were carried out in order to uncover hidden bugs, to ensure the quality of the product which enables to achieve high customer satisfaction on live operation. By following standered software development methods, following set of categories of tests were carried out.

* Unit Testing
* Integration Testing
* System Testing
* Regression Testing

Also, it was taken necessary steps to fix the identified bugs throughout the testing process and was able to ensure that the final product is working as per the requirements.

### **Test Cases**

Followings are set of test cases which were conducted for learning material recommendation and learning content identification component, under the system testing step of the testing process.

Table 4.1 Test Case - Add new module

|  |  |
| --- | --- |
| **ID** | **001** |
| Test Case Name | Add new module |
| Test Scenario | Add new module to the LMS by the Teacher |
| Primary Actor/s | Teacher/Tutor |
| Preconditions | Tutor must be logged in to the teacher dashboard of the AITor |
| Input Data | * Module basic information * Module outline of the module |
| Test Steps | 1. Navigate to the “Add Module” page of the teacher dashboard. 2. Fill all the required fields of the add module form. 3. Upload the module outline of the module using “Upload Module Outline” Button on the form. 4. Click submit button. |
| Expected Output | * New module should be appeared on the modules section of the teacher dashboard. * New module should be appeared on the modules section of the student dashboard. |
| Actual Output | * Shows added module on the teacher dashboard. * Shows added module on the student dashboard. |
| Status (Pass/Fail) | Pass |

Table 4.2 : Test Case - Identify learning content using module outline.

|  |  |
| --- | --- |
| **ID** | **002** |
| Test Case Name | Identify learning content using module outline. |
| Test Scenario | System should be able to identify the learning areas of the module by module outline document. |
| Primary Actor/s | Teacher/Tutor |
| Preconditions | * Tutor must be logged in to the teacher dashboard of the AITor * Module outline document should be in “pdf” format. * Module outline document should be in written in given format of the AITor user manual. |
| Input Data | Module Outline Document |
| Test Steps | 1. Navigate to the “Add Module” page of the teacher dashboard. 2. Fill all the required fields of the add module form. 3. Upload the module outline of the module using “Upload Module Outline” Button on the form. 4. Wait for upload progress bar to complete. 5. Click on “View Identified Content” Button. 6. Compare with main learning areas of the module outline document with the identified learning areas. |
| Expected Output | Identified learning areas should be same as in the main learning areas of the module outline document. |
| Actual Output | Identified learning areas are same as in the main learning areas of the module outline document. |
| Status (Pass/Fail) | Pass |

Table 4.3 Test Case - Populate module page.

|  |  |
| --- | --- |
| **ID** | **003** |
| Test Case Name | Populate module page. |
| Test Scenario | Module page should be populated according to the learning content identified by the module outline. |
| Primary Actor/s | Teacher |
| Preconditions | Tutor must be logged in to the teacher dashboard of the AITor. |
| Input Data | * Module Outline Document |
| Test Steps | 1. Navigate to the “Add Module” page of the teacher dashboard. 2. Fill all the required fields of the add module form. 3. Upload the module outline of the module using “Upload Module Outline” Button on the form. 4. Wait for upload progress bar to complete. 5. Press Submit button. 6. Navigate to the module page of the newly added module. 7. Compare the sections of module page with the mail learning areas of the module outline document. |
| Expected Output | Sections of the respective module page should be same as in the main learning areas of the module outline document. |
| Actual Output | Sections of the module page is same as in the main learning areas of the module outline document. |
| Status (Pass/Fail) | Pass |

Table 4.4 : Test Case - Recommend learning materials according to identified learning content.

|  |  |
| --- | --- |
| **ID** | **004** |
| Test Case Name | Recommend learning materials according to identified learning content. |
| Test Scenario | System should be able to recommend learning materials according to identified learning content. |
| Primary Actor/s | Student |
| Preconditions | * Student should be logged in to the system. * Student should be enrolled into the respective module |
| Input Data | N/A |
| Test Steps | * Navigate to a module page in enrolled module list. * Click “View Recommendations” link at the bottom of any section on the module page. * User will navigates to the recommendations page. * Ensure Audio, Video and Text based recommendations are appear in the recommendations list. * Compare the topic of selected section of the module page and similarity of the materials recommended for that section. |
| Expected Output | Recommended learning materials should be match with the expected learning content of the selected section of the module page. |
| Actual Output | Recommended learning materials match with the expected learning content of the selected section of the module page. |
| Status (Pass/Fail) | Pass |

Table 4.5 : Test Case - Recommend learning materials for new users.

|  |  |
| --- | --- |
| **ID** | **005** |
| Test Case Name | Recommend learning materials for new users. |
| Test Scenario | New user will be enrolled to existing module.  System should be able to recommend best rated learning materials to new users. |
| Primary Actor/s | Student |
| Preconditions | * Student should be logged in to the system. |
| Input Data | N/A |
| Test Steps | * Enroll to an existing module in the modules page. * Select a section and click on “View Recommendations” link. * Check the AITor ratings section of the recommendations. |
| Expected Output | System should recommend best rated items in the AITor system for the selected learning content. |
| Actual Output | System recommends best rated items for existing modules in the AITor system for new users for the selected learning content. |
| Status (Pass/Fail) | Pass |

Table 4.6 : Test Case - Recommend learning materials for existing(Trained) users.

|  |  |
| --- | --- |
| **ID** | **006** |
| Test Case Name | Recommend learning materials for existing(Trained) users. |
| Test Scenario | Trained user will be enrolled to existing module.  System should be able to recommend learning materials recommended using collaborative filtering. |
| Primary Actor/s | Student |
| Preconditions | * Student should be logged in to the system. * Student should previously enrolled at lease one module of the system of the system and should have provided ratings. |
| Input Data | N/A |
| Test Steps | * Enroll to an existing module in the modules page. * Select a section and click on “View Recommendations” link. * Compare the recommendations with the recommendations for a new user. |
| Expected Output | System should able to produce fine-tuned and more personalized recommendations for existing and trained users. |
| Actual Output | Recommendations for the existing user is different than the recommendations for the new user. |
| Status (Pass/Fail) | Pass |

## **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 5.7: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.

# **RESULTS AND DISCUSSION**

At the end of the implementation, the system was able to function as it was expected and was able to predict learning styles, recommend learning materials according to the predicted learning styles, identify best suited career paths and to provide accurate forecasts of students in different levels. Individually the learning style identification component was able to record 86.67% of accuracy while learning material recommendation module and skill Identifier and career path recommendation modules respectively preserving 83.58% and 83.35% average values.

In measuring the accuracy values for the material recommendation component, it had to use survey-based approach since this component has been used unsupervised learning for the model implementation. In this process, separate survey was created to get feedbacks od users who was got learning material recommendations via the material recommendation component. By comparing recommended ratings for learning materials and actual ratings which was gathered through the survey, the accuracy values were calculated.

Another factor that was highly affected towards the accuracy of the material recommendation model was the sparsity of the learning materials of some of the types. Compared to the video and text-based learning materials, the sparsity of audio learning materials was very high, and this effect resulted in introducing difficulties in recommending learning materials as per the predicted weights of different learning styles.

As it was introduced in aforementioned, having a rich pool of learning materials always empowers the learning material recommendation systems more accurate and the current accuracy values will be further increased through exposing to high number of learning materials.

# **CONCLUSION**

Irrespective of the learning methodology (distance learning or in class education), achieving personalization in education was highly challenging. This study was basically focused on finding solution to personalization challenge through a machine learning based method and to build a learning platform which personalized according to personal learning styles. This intention was achieved in this study through recommending and providing learning materials according to personal learning styles. A collaborative filtering and machine learning based hybrid learning material recommendation system was introduced and this recommendation system was integrated with Dynamic Weighted Probability Allocation (DWPA) which is used identifying learning styles. By combining above models, the system as a whole provides the personalized learning materials that are highly matched with learner’s personal learning styles.

## **GANTT CHART**

**Chart, waterfall chart

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Table 7.1: Gantt Chart

# **REFERENCE LIST**

[1] S. Kumar Basak, M. Wotto, and P. Bélanger, “E-learning, M-learning and D-learning: Conceptual definition and comparative analysis,” *E-Learning and Digital Media*, vol. 15, no. 4, pp. 191–216, Jul. 2018, doi: 10.1177/2042753018785180.

[2] V. D. Soni, “Global Impact of E-learning during COVID 19,” *SSRN Journal*, 2020, doi: 10.2139/ssrn.3630073.

[3] T. Sheeba and R. Krishnan, “Prediction of student learning style using modified decision tree algorithm in e-learning system,” in *Proceedings of the 2018 International Conference on Data Science and Information Technology - DSIT ’18*, Singapore, Singapore, 2018, pp. 85–90. doi: 10.1145/3239283.3239319.

[4] “Bezhovski and Poorani - 2016 - The Evolution of E-Learning and New Trends.pdf.” Accessed: Jan. 23, 2022. [Online]. Available: https://eprints.ugd.edu.mk/15692/1/The%20Evolution%20of%20E-Learning%20and%20New%20Trends.pdf

[5] E. El Bachari, E. H. Abdelwahed, and E. M., “E-Learning personalization based on Dynamic learners’ preference,” *International Journal of Computer Science and Information Technology*, vol. 3, pp. 200–216, Jun. 2011, doi: 10.5121/ijcsit.2011.3314.

[6] M. Salehi, I. N. Kmalabadi, and M. B. G. Ghoushchi, “A New Recommendation Approach Based on Implicit Attributes of Learning Material,” *IERI Procedia*, vol. 2, pp. 571–576, 2012, doi: 10.1016/j.ieri.2012.06.136.

[7] M. Salehi, I. Nakhai Kamalabadi, and M. B. Ghaznavi Ghoushchi, “Personalized recommendation of learning material using sequential pattern mining and attribute based collaborative filtering,” *Educ Inf Technol*, vol. 19, no. 4, pp. 713–735, Dec. 2014, doi: 10.1007/s10639-012-9245-5.

[8] “An association rule based recommender system for learning materials recommendation.” https://vpn.sliit.lk/proxy/11ea7a12/https/ieeexplore.ieee.org/document/9470635 (accessed Jan. 04, 2022).

[9] F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, “Recommendation systems: Principles, methods and evaluation,” *Egyptian Informatics Journal*, vol. 16, no. 3, pp. 261–273, Nov. 2015, doi: 10.1016/j.eij.2015.06.005.

[10] F. Liu and B. Shih, “Learning Activity-Based E-Learning Material Recommendation System,” in *Ninth IEEE International Symposium on Multimedia Workshops (ISMW 2007)*, Taichung, Taiwan, Dec. 2007, pp. 343–348. doi: 10.1109/ISM.Workshops.2007.64.

[11] F.-J. Liu, “Design of Self-Directed E-Learning Material Recommendation System with On-Line Evaluation,” in *2008 International Conference on Convergence and Hybrid Information Technology*, Daejon, South Korea, 2008, pp. 274–277. doi: 10.1109/ICHIT.2008.184.

[12] S. Moghavvemi, A. Sulaiman, N. I. Jaafar, and N. Kasem, “Social media as a complementary learning tool for teaching and learning: The case of youtube,” *The International Journal of Management Education*, vol. 16, no. 1, pp. 37–42, Mar. 2018, doi: 10.1016/j.ijme.2017.12.001.

[13] M. M. Rahman and N. A. Abdullah, “A Personalized Group-Based Recommendation Approach for Web Search in E-Learning,” *IEEE Access*, vol. 6, pp. 34166–34178, 2018, doi: 10.1109/ACCESS.2018.2850376.

[14] N. N. Qomariyah and A. N. Fajar, “Recommender System for e-Learning based on Personal Learning Style,” in *2019 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, Yogyakarta, Indonesia, Dec. 2019, pp. 563–567. doi: 10.1109/ISRITI48646.2019.9034568.

[15] “80,000 fail AL exam due to wrong selection of subject stream - Front Page | Daily Mirror.” https://www.dailymirror.lk/front\_page/80-000-fail-AL-exam-due-to-wrong-selection-of-subject-stream/238-163708 (accessed Feb. 09, 2022).