**AITor: AI Solution to assist online education productivity via personalizing learning strategies and analyzing the student performance**

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DECLARATION

We declare that this is our own work, and this proposal does not incorporate without acknowledgment 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 acknowledgment is made in the text.

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ABSTRACT

Higher productivity in online education can be attained by consistent student engagement and appropriate use of learning resources and methodologies in the form of audio, video, and text. Lower literacy rates, decreased popularity, and unsatisfactory end-user goals can result from unbalanced or inappropriate use of the aforementioned. Prior studies mainly focused on identifying and separating the elements affecting the quality of online education and pinpointing the students' preferred learning styles outside of in-person and online instruction. This has not been able to clearly show how to enhance and customize the online learning environment in order to benefit the aforementioned criteria. This case study will primarily concentrate on elements that can be personalized and optimized to improve the quality of online education. With the aid of various algorithms like logistic regression, Support Vector Machines (SVM), time series forecasting (ARIMA), deep neural networks, and Recurrent Neural Networks (RNN), which make use of machine learning and deep learning techniques, the ultimate result has been attained. To increase application and accuracy, the newly presented technique will then be presented as a web-based software application. Contrary to what is commonly believed, this applied research proposes a new all-in-one Learning Management System (LMS) for students and tutors that acts as a central hub of all the learning resources.

ACKNOWLEDGEMENT

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INTRODUCTION

Within the last few years, there has been a significant shift in the idea of traditional schooling. With the development of the internet and new technology, attending classes in person is no longer the only way to study. As long as you can access the internet, you can acquire a good education today whenever and wherever you want. A new age has begun with the transformation of online learning. Therefore, based on current technological trends and advancements, it is safe to say that distance learning will eventually replace in-class education and provide every student with the best and most productive education possible, regardless of their social or political problems.

Nevertheless, as a result of the widespread COVID-19 pandemic, most of the teaching-learning activities have been shifted drastically online. As a result, most educational institutes, students, and tutors started to use Content Management Systems (CMS) and Learning Management Systems (LMS). However, as a result of this rapid adoption, it has brought to light that the vast majority of students and instructors are struggling with issues relating to their levels of productivity, imbalance of course content or learning materials, inability to analyze the progress and inefficacy to align the students' learning curve with the current industrial requirements and trends.

Given the above reasons and problems, this case study is mainly focuses in how to eradicate the aforementioned problems with the help of artificial intelligence and other supportive ICT technologies.

For the ease of implementation, the entire case study has been de-structured into four main subtopics as

* Personalizing the learning strategy if an individual student
* Recommending the best leaning materials to the students
* Student’s performance/productivity calculation
* Student career guidance

Focusing on, personalizing the learning strategies of the students, it has been identifying that, this contributes a significant percentage towards the productivity of the online education. When it comes to the factors that are affecting the productivity of online education, various health conditions of the student and the personal preference of the learning strategies of a student, the types of devices students are using to learn in online education, and the literacy of usage of IT-related methodologies can be highlighted as some of the most important factors. It has been said again that it is critical to pay attention to the consistent delivery of content because it is dependent on the type of device the student is using and how well they know how to use IT-related tools.

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 1.2: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 1.3: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.

The IT industry has shown rapid growth over the last few decades with a number of growing career opportunities. Since the IT industry provides a wide range of career paths, when stepping into the industry, freshers may get confused about which path to select as their career. According to research conducted by Peter Akosah \cite{akosah-twumasi\_systematic\_2018}, there is a chance of getting wrong decisions on career path selection due to some external factors such as family pressure, friend's career, and social pressure. Therefore, having a clear understanding about their own capabilities and personal interest is important when choosing a career path as a fresher. Many Students start their first career after they completed the higher education or during the higher education. This stage can be considered as a key point of the person's career life since it's the first time they take the decision of their career path. Therefore, it is important to provide appropriate guidance to the students prior to their entry into the industry. Number of research has been conducted focusing on career path identification and career guidance.

## **Background Literature**

According to the previous case studies that has been conducted before, it can be identified that there is a rising amount of research conducting the practices to provide a quality and productive online education to students. in accord with the literature survey, it was able to identify that, the above-mentioned factors in the introduction are the main factors affecting to the quality and the productivity of the online education.

According to a case study conducted by Sindiani, Amer Mahmoud, et al on the topic of "Distance Education During the COVID-19 Outbreak: A Cross-Sectional Study Among Medical Students in Jordan" , 2212 out of 3700 students, or 55.8 percent, began to engage with online lecturers after 3 weeks of the module's start date. Another 31.4 percent learned from live lectures, and 22.8 percent gained the most from recorded lectures. The preceding case study concentrated mostly on medical students at Jordan University of Science and Technology (JUST). In conclusion, the survey found that the majority of students favored traditional face-to-face learning over online education, and they advised that online education be improved by personalizing the system with well-established infrastructure and learning methodologies.

Furthermore, it has been mentioned that there is a positive correlation between productivity and self-regulated learning strategies in a case study that was carried out by Daeyeoul Lee, Sunnie Lee Watson, and William R. Watson on the topic of "The Relationships Between Self-Efficacy, Task Value, and Self-Regulated Learning Strategies in Massive Open Online Courses" [2]. With the use of Pearson's correlation analysis, the case study was able to demonstrate the distinction between high levels of self-efficiency and low levels of self-efficiency.

Yang Tzu-Chi has done research on how observational learning and self-regulated learning strategies can affect the online learning performance of student [3]. The case study has focused on how observational learning (OL) and self-regulated learning (SRL) can link up with the online learning strategies. With the research context, it was identified that, the learning performance can be positively altered with proper identification of behavioral patterns of the student. [3]. Furthermore, the implemented system has dual proposed mechanisms to support both OL and SRL [3]. It includes, setting and externalizing the goals, planning the learning strategies and the time student is willing/planning to study a particular subject area. The study was conducted in a classroom, with 2 main assessment tests as pre and post tests. All the students were made aware about the procedure which includes weekly online tests, after each lecture was delivered. Before the weekly assessments, the students were made to face a classic-type examination and after the online tutoring, there was another post-test to attend. With the experimental results, it was highlighted that there is no clear relationship between OL and SRL. Furthermore, it has identified that, students with SRL strategies have high performance in learning.

Jim B.J.Huang et al has done a research on exploring the learning strategies by sequence clustering and analyzing their correlation with student’s engagement and learning outcome [5]. This case study has followed and iterative process of collecting and analyzing data to fine-tune the identification of the strategies. They have used, pre-defied questions and interviews to collect the data. With the test results, they were able to identify the learning strategy by the logs of the student test results, identify the relationship between learning strategy and learning outcome. The research was done with 53 college students with the data of python course. the questionnaire developed by the Elmaadaway [4] has made with 3 sectors covering behavioral, cognitive and emotional engagement.

Fidelia O. and Et al have done research [13] on how finding a relationship between students engagement and his/her performance. They have primarily focused on Total time spent in MindTap (TimeOnTask), Number of logins, Percentage of Activities Accessed features when building up the relationship. They have used both supervised learning (Random forests) and unsupervised learning (clustering) models to fine-tune the final output.

Furthermore, according to a review article which is referenced at [7] and done by David Bueno, there are three main contributing factors that influence the satisfactory level of online education. They are "Online Learner Factors", "Online Instructor Factors" and "Online Platform Factors". Since this case study is mainly focused on optimizing the learner experience, more attention has been paid to the factors such as gender, age, health problems, and device types, which fall under the online learner factors. It has been concluded that the aforementioned factors have different levels of contribution towards the productivity of online education.

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.

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.

Number of research has been conducted focusing on providing more efficient career path identification and career guidance for university students. Those studies have focused on identification of student’s skills and providing the most suitable career guidance by analyzing the student profile following various machine learning approaches.

Vignesh S, Shivani Priyanka and Shree Mangju have come up with a career guidance system for the engineering students based on their skills[1]. They have conducted an assessment to evaluate the student skills, which includes psychological and the core-skill oriented questions. Students have been clustered into different departments (computer science engineering, electric and electronic engineering, electronic and communication engineering, and mechanical engineering) based on the identified skills with the help of the K-means clustering algorithm.

In 2014 team of researchers with Tajul Rosli, have implemented a career path recommendation system using fuzzy logic, [2] focusing on computer and mathematical students. In addition to the student’s technical skills, they have considered the student’s personality as well. Personality and skills data were collected through a series of interviews. Skills have been labeled with three linguistic variables which are ”Good”, ”Medium”, and ”Weak”. Considered careers are also labeled, respective to the student, with another three linguistic variables which are ”Yes”, ”No”, and ”maybe.

Ashutosh Shankhdhar, Akash Agrawal and Deepak Sharma have come up with an intelligent decision support system using the decision tree algorithm. [3] They have collected student academic performance through a survey and some quizzes to collect data about student personality. In this study also, student personality was considered in addition to technical skills. Decision tree algorithm have been used to identify the most suited career for the student.

In terms of candidate profile classification, numerous research has been conducted using text classification techniques.

Razkeen Shaikh, Nikita Phulkar,and Harsha Bhute have implemented a system to classify the candidate by analyzing the profile using text categorization and semantic analysis. [4] Recommendations have been given by calculating the similarity between candidate skills and the required skill set.

## **Research Gap**

From the aforementioned case studies, it can be identified that, most of the time, self-regulated learning (SRL) has a positive correlation between productivity of the education. Not to mention, none of the case studies were able to conclude a better way to optimize the SRL. The approach presented here will help to overcome the above barrier by personalizing the SRL contributing factors. Furthermore, none if the case studies have focused on any of the health-related issues, students may have when implementing their solutions in the applications. But the online survey we done, it can be highlighted that, majority of students have some sort of focus related issue when it comes to the online learning. In most of the cases, main reason students are reluctant to join with live lectures is, the time frame a lecture could expand and the level of engagement it has. Considering the case studies that has been done in the domain, none of the case studies have a contributing feature to assess the student’s health conditions before fetching them the learning materials. Further, none of the real-world applications implemented, does not have a feature to evaluate/re-evaluate the health factors of a student.

Not only that, according to the case study, we were able to identify nearly 30% of the population of LMS users does not have a proper knowledge of how to use a computer in a more productive manner. Elaborating the above statement more, 80% of the above 30% are tutors and lecturers. Furthermore, students who are using mobile devices to connect with their live lectures and access the lecture materials have low productivity than those who uses a laptop or a personal computer. after some reserch on this, it was able to identify that, the screen size plays a major role to achive a higher productivity. However none of thr case studies have foused on the device type of the users are using. Furthermore, even though most of the learning management platforms are responsive, none of them have any inbuilt functions to specifically address the above concerns.

Given the fact that, this case study is more focused on finding and personalizing the learning strategy of each students, these concerns have to be addressed thoroughly. Otherwise achieving a higher productivity in distance learning/ online education would be limited.

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 |

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.

By examining existing career guidance systems, the student skill identification phase is usually performed by analyzing student academic data or conducting the interviews and quizzes. When the student grades are evaluated module-wise, it won’t be able to get accurate data on individual skills of the student. Students’ career paths may be changed by the skills they gain through the learning process, and it is important to give them an idea about how should they align their career path accordingly. None of the above-mentioned studies have attempt to evaluate student’s skills continuously and identify the student core skills. To fill the above-mentioned gaps, this study proposes a machine learning approach based on the identification of the student skills and the IT industry-specific requirements.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Study | Consider Student’s Technical Skills | Consider Student’s Personal Skills | Consider Student’s Interest | Continuous Student’s Individual Skill Evaluation and Identification |
| Study 1 [1] | ü | ü | û | û |
| Study 2 [2] | ü | ü | ü | û |
| Study 3 [3] | ü | û | û | û |

RESEARCH PROBLEM

Depending on the type of course and the program type, whether it's full-time or part-time, students are required to spend a considerable number of hours on the course content. With online education, this number may have been increased. From the closed survey done, it can be identified that most of the students are spending 10+ hours in their course content. Refer to Figure 1.7 for more information.

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Figure 0.1Number of hours students are engaging in online education

Furthermore, according to [14], students’ behavior and emotional engagement are highly effective to the final productivity of the education. In the context of [1], learning resources and learning style/strategy is a direct influencing factor for a highly effective online education.

Further to the results acquired by the survey, Figure 1.4 includes the different ways of learning strategies students are using to gather the required knowledge. Although predicting the best-suited learning strategy of each student is somewhat qualitative and highly volatile, this case study will aim at predicting it by combining user feedback analysis and rapid assessment evaluation methodology.

The case study will provide a high-level overview of how knowledge-inspired computing can be used in the educational sector in order to enhance, predict and analyze the students learning strategies in online education. By usage of pattern recognition and unsupervised learning algorithms, the AITor application is loaded with a technology-enhanced fine-grained learning strategy prediction feature.

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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.

For a university student, Identification of suitable career path is a critical decision as a newcomer to the industry. Even the student has followed a specific subject stream targeting specific industry, since an industry provides multiple career paths focusing on specific skills and requirements, selecting  the most suitable career path can be quite challenging. Without a proper understanding about industry requirements and their own capabilities, it may lead to incorrect decisions.

Addition to that, family pressure, friends’ career and social pressure can directly make impact to the student’s decision on career path selection. With these impacts, a student may be able to select a wrong career path and then he or she will have to face many difficulties in career life. Having to work with technologies and tools which are not interested in, not able to work with others in similar capacity kind of concerns will push the student to very difficult situations and it can be worst when they have to balance both work and academic life.

As a solution for this problem, a career guidance system is developed attaching to the machine learning based learning management system “AITor”. It will be able to analyze the student skills continuously and identify the core skills and then, based on those identified skills and student personal interest, it will suggest the most reasonable career path. Addition to that system will suggest the most suitable job openings for the student according to the above-mentioned parameters.

RESEARCH OBJECTIVES

## **System Objectives**

Identification of student core skills through continuous assessment series and the identify the most reasonable career path for a student using machine learning model based on above identified skills and then suggest the most suitable job openings for the student by matching the required skills and the student skills.

## **Main Objective**

Identify the core skills of IT undergraduate students including both technical and personal skills, then provide an efficient career guidance for them considering their personal interest also. As the main output, this will suggest the most suitable career path for the student and the current job openings

### **Specific objectives**

1. Identification of the best learning strategy
   1. This objective is to scheme out the mechanism of how the application is going to identify, predict and analyze the suited learning strategy/s of the student. Authors have to research and decide the available and most used learning strategies from the students. This includes building up and testing up the hypothesis of how to find the optimal learning strategy if each student. In most cases, one student may have an array of learning strategies (video, audio, text). This objective should address those requirements as well. Furthermore, this objective includes the way of implementing the above features in the AITor web application. Authors will have to consider best practices and best UI/UX principles when implementing those features. Apart from that, to address privacy, proper consent should be received from the user. This objective will address the proper provision of guidelines and methodologies that are up with current industry norms. Those all requirements should be achieved through the web application and, to provide seamless implementation the features will be implemented by following agile methodologies. This will include incremental implementation with time-bounded deadlines.
2. Student Skill Identification
   1. As the first step of the career guidance system, students core skills will be identified by the system. This will perform through a continuous assessment process and skills will be updated with the student progress. Both technical and personal skills will be analyzed by the examination module.
3. Career path identification
   1. According to the skills identified, the student will be recommended current industry trending careers.
4. Job Opportunity Recommendation
   1. Based on identified skills and the suggested career path, student will be recommended current job openings.

METHODOLOGY

## **Introduction and Basic User Flow**

### **Identification of learning strategies**

The case study is proposing a full scalable web application that has the capability of;

* Analysing, identifying and predicting the best learning strategy/s of a student
* Recommending course related materials according to the identified learning strategies
* Asses the student with the standard assements provided by the tutor and analyse them.
* Identify the potential skills of the student related to computer science.
* Provide detailed analysis of each student as well as entire batch of the student to the tutor or to the institute

This section will mainly focus on how to implement the extraction of best learning strategy of the student via the web application.

With the knowledge gain from the literarture study, it was able to identify that, most of the case studies or applied researches have only considered implementing featuers to either extract the engagement percentage or the learning strategies. For engagement analysis, most of the studies have used facial emotional analysis and for learning stragey identification, majority of the studies have collected data via online questionires, past assessment grades and surveys. However it is clear that there should be a significant relationship between the engagement and the learning strategy.

The proposed feature includes combinantion of engagement analysis, questionire review and assessment review. The model will evaluate each input and based on statistical proof, the ideal learning strategy/s will generate. This actions will cope with generating highly accurate results compared to the studies done in the above.

Furthermore, the proposed model is consiste of two major sub-sections namely

1. Pre-evaluation stage
2. Post-evaluation stage

Figure 3.1 includes the high-level overview of how inputs of  this two sub-section will implement and interact with each in the proposed web application.

Diagram

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The post-evaluation stage is interacting with the marks get by the students in their day-to-day assessments. If the marks are getting low by the time, it will re-iterate the above process and will fine-tune the results get by the pre-evaluation stage.

Features and responsibilities of each sub-modules can be brief as follows.

1. Pre-evaluation stage

this feature is fully web based dynamic interface that the student will directly interacting with. If the user is new to the system, the user will navigate through a pre-defined path in order to get the basic information and surey data. A well defined consent will take in this stage, since the data gatherd in the basic information and the survey has some privacy concers. After a successful provision of above data and information, the student will be undergo an pre-defined set of proceduers. As the first step, the student will be taught a set of theory concepts upon the selection of the theory via the identified three means of learning strategies (video, audio, text). Then an immediate assesment will be provided to the student to assess the competency level of the student related to the content covered in the above three learning strategies. Upon assessing the assessment, the dynamic engagement analysis and learning strategy identification model will evaluate the student and predect the suitable weights/percentages of the learning strategies that the particular student should be labeled. Figure 3.4 will brief how the user flow will takes place in the above scenario.

Diagram

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1. **Proposed Technologies**

Since this is the first interface, user is interacting with, the number of data collected in the system is less. Therefore the proposed plan is to make the suggestions/predections in more of a high level and then, closely monitor student and re-asses the parameters whenever possible and needed. Due to the lack of past data of the particular student regarding the learning strategies, a simple survey will be conducted to gather high-level undersating about the way the student is comfortable with learning online. With the data collected from the closed survey, then the student will labed into three main catagories according to the confident level of the learning strategy.

Form the case studies [15], [11], [16] it has been identified that many of the authors have used conventional methods such and rely on the past assessment data of the student and machine learning teqniques to build up a valid hypothesis of the domain.

In this applied research, since it is aimed to follow combinantion of engagement analysis, questionire review and assessment review mechanism, a wide online survey is proposed to conduct among school and university student. The colleted data will be used to identify the future students who are registering with the system.

Here the student get a percentage related to each and every learning strategy (Video. Audio, Text), one student may fall under one or more categories. Therefore, an un-supervisoed multy-clustering method is proposed to use in both level 1 lerning strategy identification module as well as dynamic engagement analysys and leranig strategy identification module.

The final result is proposed to have a possibility percentatges on how each and every student is belong to each learning strategy cluster. The figure 3.4 shows how the possibility percentage weight factor(PPWF) will be calculated.

Text BoxChart, scatter chart

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1. **Requirement gathering**
2. **Data gathering and pre-processing**

With the emergence of web 3.0 and new technologies, there are wide range of supportive content materials out in the internet. Therefore, it is mandatory to reaserch and identify potential and most used content types that the students are using. According to the figure 1.4, it was identified that most of the students are well enaged with learing subject matters via a video content, audio content or text based content. Since as the primary learning strategies, for this case study, it will aim on categorizing the students to each strategy based on their perfomace and the personal choice.

Before labeling the student with possibility weights of the learning strategy, identification of potential learning strategies most of the sudnets are currently using is a must. Doing that so will help to mitigate the noise in developing the related algorithems and categorizing the future students.

In the data collection phase, a wide open online survey is proposed to conduct covering samples from

* University students
* Schools students
* Private sector tution class students

The questionire is propsed to include both qualitative and quantitatvive questions regarding the types of contents the students are following to learn online.

Apart from that, once the students is registerd in the system, a periodic random test will test the productivity of the student by evaluating the grades that the student is getting from the assignments. If there is a requirement, a separate questionire will provide the student to answer. From that the previous posibility weight factors will be fine tuned.

1. **What is proposed to achieve from the data set**

The data collected from the data collection will be primarily used to identify the demand for each and every strategy that the students are using and train the algorithem that will be implemented to assign the studenst with the probability weight factors.

1. **Feasibility study**
2. **Implementation feasibility**

The methodology of implementation is proposed to follow with the software engineering best practices and frameworks. The software implementation will proposed to follow an agile method where if there is a prioritization is required “Kanban” practice to be used.

1. **Technical feasibility**

In order to achieve high accuracy and dynamic behaviour of the percentatge weight factor, usage of machine learning technologies is proposed. Due to the inadequativity of the quantitative data about each and every student in the first stages, a unsupervised classification model is planned to use. Eventhough to have a high accuracy in the final output, combination of statistical analysis methodologies or machine learning methodologies is proposed.

1. **Implementation**

The implementation phase includes

* Implementing the probability weight factor calculation model
* Implementation of the basic back-end
* Implementation of the data access layer
* Implementation of the font end
* Deployment

The entire application will be implemented within the microservice architecture.

To maintain the consitancy in the development and deployment, adoption to DevOps is proposed. As an initial step, a proper implementation of CI/CD is proposed. To achive a high availability and prevent potential data loss, the application will be de-coupled with the help of message queues. The intention of implementing a separate data access layer is to provide extra security to the data flowing throughout the application and have a consistency of the CRUD operations.

1. **Deployment**

The proposed application will be fully cloud native and will use Amazon Web Servises(AWS) as the go-to cloud provider. The application will use managed services of AWS to achive high availability and regulatory. Since the application is planned to adopt with DevOps a proper CI/CD imlmenetation is propsed to implement. All the components will be containerized with the help of Docker technologies.

Diagram

Description automatically generated

This section describes the implementation of the career guidance system which consists of three main modules.

• Student skills and personal interest identification   
• Career path identification   
• Career opportunities recommendation

1. **Student skills and personal interest identification**

[Image]

In the initial stage, which is the preparation phase of the exam paper, all the questions in the exam paper will be tagged according to the required skills. Some existing studies have proposed this content tagging concept [10] for student skill identification, which can be used to address the above-mentioned problem, which is the difficulty of getting accurate data on student performance of individual skills. These skills can be technical skills, such as programming languages, frameworks, and databases, or soft skills, such as problem solving, analytical, and critical thinking skills. One question can be  tagged with one or multiple tags. The tags are predefined and available in the preparation of the exam paper.

|  |  |  |
| --- | --- | --- |
| Skill | Category | Type |
| Java | Language | Technical Skill |
| React JS | Framework | Technical Skill |
| Problem Solving | - | Soft Skill |

Second phase, examinations will be conducted through a online examination platform and obtained marks for each and every question will be recorded. In the 3rd phase, examination results will be evaluated and average mark for each and every skill will be calculated. Based on the average mark, skills will be graded. If the skill has expected grade level or above, it will identify as a core skill of the student. Another important factor mentioned above is the student’s personal interest. Even if the student showed better performance in different subject areas, it can’t assume that the student is preferred in all of them. This system has implemented a feedback mechanism to collect the student’s personal preferences in covered subject areas and any other related subjects. Student can rate their experience on covered learning areas or input any other personal interests related to the IT industry. Those ratings will be saved along with previously identified skills. Then, the intersection of the previously identified core skill set and the student’s most preferred skill set will be extracted as the optimal skill set for the career recommendation.

1. **Career Path Identification**

Career path identification model has been implemented as a multi-class text classification model to take the student profile as the input and to recommend the most suitable career as the output. The student profile is maintained by the system in four aspects. Technical skills which are identified by the system, skills determined by the student, student career-related personal interests, and the personal skills of the student. Here, students are allowed to add skills to their profile since a student can have some skills in addition to what they learn in the academic subject stream. The following table showcases an example of a prepared student profile by the system.

1. **Career opportunities recommendation**

Career opportunities recommendation module was implemented that focuses on recommending career opportunities in the IT industry by matching the set of identified student skills with the skills extracted from job postings. Here the identified career path in the second step will be an optional parameter to recommend the career opportunities since career opportunities recommendation was focused on the recommendation of job opportunities based on student skills and experience level. Student can determine their experience level in the system. Job postings will be classified into three categories based on the required experience level.

|  |  |
| --- | --- |
| Job Position/ Description | Experience Level |
| Intern/ Trainee | Entry level |
| Associate or 1-5 exp | Mid-level |
| Senior/ Lead or exp > 5 years | Senior level |

A picture containing table

Description automatically generated

The Jaccard similarity index compares values for two sets to identify which values are shared and which are distinct. The similarity will be given in range of 0\% to 100\%. Based on the calculated similarity, most suitable job opportunities will recommend for the student. In this system, it was designed to recommend jobs that have similarities of 50\% or above.

## **Data gathering**

In the data collection phase, it considered gathering data on various careers in the IT industry and their requirements. This research has been narrowed down to the below careers which are demanding in computer science and that can start as a fresher.

* Backend Developer
* Database Administrator
* Data Scientist
* Database Administrator
* Devops Engineer
* Frontend Developer
* Fullstack Developer
* Mobile Application Developer
* Network Engineer
* Software Quality Assurance Engineer
* Security Analyst
* UI/UX Designer

The data set was prepared with existing data sets that contain job postings in the last few years. From the selected data sets, IT industry-related job postings were separated, and since some job postings contain entire job descriptions, skills were extracted using keyword extraction techniques. The data collected was organized as required skills along with the career path/position. Data points that contain null values or insufficient job descriptions have been removed. The extracted text data was converted to a matrix of token counts using Count vectorizer. Finally, the count matrix was transformed to a normalized tf-idf representation using TfidfTransformer. The table below describes the structure of the data set.

|  |  |
| --- | --- |
| Career | Required Skills |
| Frontend Developer | JavaScript, React, HTML, CSS, SCSS, Designing, CI/CD, REST API, Git |
| Backend Developer | Java, MySql, Spring boot, AWS,Git, problem solving skills, Analytical skills |
| Mobile Application Developer | Flutter, Firebase, NodeJs, Swift, Cordova, Analytical skills |
| Backend Developer | Tomcat, Linux, JBoss, JSP, Eclipse, MySQL, Agile, JDBC |
| UI/UX Developer | Adobe Photoshop, UI/UX, Adobe XD, communication, graphic designs, wireframes |

## **Model Selection**

Three machine learning algorithms have been considered in the model selecting phase.

* Naive Bayes
* Support vector machine
* Logistic regression

The following figures show the comparison between different algorithms in terms of accuracy and f1 score.

In the model selection phase, three main supervised machine learning algorithms were considered for the classification model, which are Naive Bayes, Logistic regression, and Support vector machine. Support vector machine (SVM) algorithm was tested out with four kernels which are linear, polynomial, sigmoid, and RBF.

As described in the above figure, the support vector machine algorithm with the RBF kernel has shown the highest accuracy, which is 83\%. Support vector machine is a supervised machine learning algorithm used for both classification and regression problems.

SVM doesn't support multiclass classification natively and supports for binary classification. To apply SVM for a multiclass classification problem, here it has followed an approach that divides the data points in the particular class and rest, which called as one to rest approach. It can consecutively a certain class is distinguished from all other classes.

A particular type of Gaussian kernel, called a Radial basis function kernel (RBF kernel) projects high-dimensional data and searches for a linear separation for it. Based on the results of the evaluation phase, the SVM with an RBF kernel was chosen since it has shown the highest accuracy and, furthermore, has shown better performance in previous studies in multiclass text classification

**Diagram

Description automatically generatedTraining the model**

The above resulted data set has been divided into the training and the testing data set, where 70\% of the data set was used as the training data set to train the model, and 30\% of the initial data set was used to test the trained model. While training the model, a pipeline has been used to work with the vectorizer, transformer, and classifier. CountVectorizer was used to convert the extracted keywords into numeric values. TfidfTransformer was used to convert the values into a tf-idf representation, which helps to determine how relevant each word is in the input phrase. Finally, model was trained with processed data to identify the most suitable career path using the SVM as the classifier.

1. **Analyzing the Student Performance, Forecasting**

# Problem understanding and data understanding

Understanding the problem and the data is essential to determine whether the Student Performance Analysis system will be successful. Problems and data understanding are established prior to system development to specify the project's goal and objectives. The shortcomings of the current systems are noted and examined for their functionality and efficacy. Following the identification of the issues, each problem's remedies are then located and gathered by additional reading and research on the pertinent research articles.

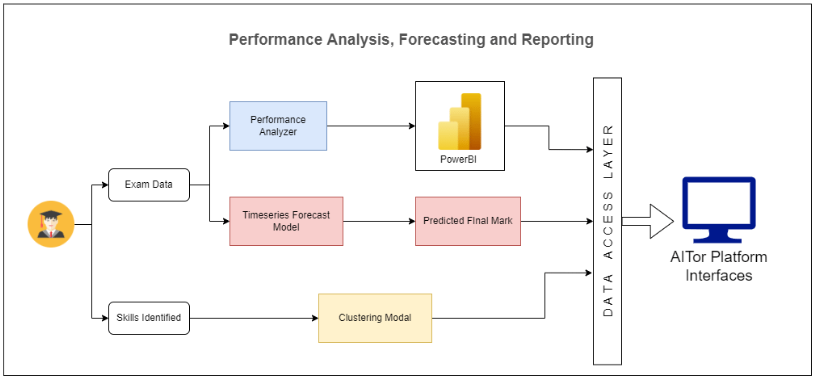
Student information is gathered in this step aside from that. Data about the students, including their semester-to-date performance on the pertinent topic module, is gathered. The characteristics of the data set gathered for data mining categorization are shown in the below table.

|  |  |
| --- | --- |
| Attribute | Value |
| Quiz for week 01 | Discrete |
| Quiz for week 02 | Discrete |
| Quiz for week 03 | Discrete |
| Quiz for week 04 | Discrete |
| Quiz for week 05 | Discrete |
| Quiz for week 06 | Discrete |
| Quiz for week 07 | Discrete |
| Mid Term Examination | Discrete, Grade |
| Quiz for week 09 | Discrete |
| Quiz for week 10 | Discrete |
| Quiz for week 11 | Discrete |
| Quiz for week 12 | Discrete |
| Quiz for week 13 | Discrete |
| Quiz for week 14 | Discrete |

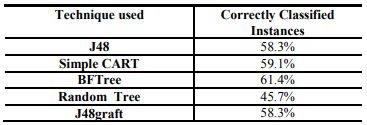
Other than these data inputs, the identified skills of the students are taken as another input for the proposed system.

# System analysis and design

The system's overall flow is planned, examined, and designed during this phase. Analyzed and listed in table style are the system and user requirements. The input, operations, and output of the system are represented on a data flow diagram. The context diagrams up to the first level's data flow diagram is analyzed and created. Additionally, a logical design of the suggested system is created to guarantee that the finished system performs as planned.

****

In order to produce IF-THEN rules for the prediction of students' results in the course "Software Process Modeling" a dataset of almost 500 student records from the course is gathered and evaluated throughout the implementation phase using data mining techniques. WEKA is a free software program that is used to generate IF-THEN rules. Training set and test set have been created from the dataset. The training set requires 80 percent of the dataset, while the test set requires the remaining 20 percent. The test set is used to evaluate the classification model's accuracy in making predictions whereas the training set is used to train the classification model. To ensure that the highest forecast of accuracy could be reached, various decision tree classification techniques are compared for accuracy. Table 2 compares the effectiveness of five distinct decision tree categorization methods that can be found in WEKA.

****

The BFTree is the decision tree classification technique used in the proposed system since it has the best accuracy (61.4 percent) of the decision tree techniques given in the table above. The WEKA best-first decision tree serves as the basis for the IF-THEN rules. The proposed system's PHP language IF-ELSE condition will incorporate these rules. Before the final test, the rules are used to forecast the students' grades in the "Software Process Modeling" course. The forecast helps the instructors identify students who are likely to fail the "Software Process Modeling" course.

The other main functional component that conducting the time series forecasting for the progress of the student will be more extracted in this part of the paper. As per discussed before in the background and literature review, it could identify that most of the case studies were considered only some of the features that we discussed on the research gap section. Most of the cases, for the time-series forecasting they did consider only in the result analysis. But to get more accurate results regarding the student’s performance, the progress analysis should also be considered in the forecasting.

In the proposed application, both the result and the progress analysis will be considered. There would be three main phases in the proposed solution to continue the process of conducting the time-series forecasting for the progress of the student, presenting the detailed report.

Before the system is deployed and utilized by IS professors, it must first undergo unit testing, system testing, and user acceptance testing to identify any flaws. This is done to make sure the system is operating at its best. Additionally, the flaws and defects found in the suggested system during testing can be rectified. To make sure the system's functionalities are operating as planned, the developer will test the system and unit code, while a small number of end users will test the user acceptance code.

References