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

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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.**

***Index Terms*—Online education, Machine learning, Deep learning, Logistic regression, support vector machines, ARIMA, deep neural networks, RNN, LMS**

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I. 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 analyse the progress and inefficacy to align the students' learning curve with the current industrial requirements and trends.

The section II of this paper focuses on the background study of the case study while the section III and section IV focuses on the methodology followed, results and conclusion of the case study.

II. LITERATURE SURVEY

Yang Tzu-Chi has done a research on how observational learning (OL) and self-regulated learning (SRL) strategies can affect the online learning performance of student [13]. According to this study, identifying a student's behavioral tendencies can improve learning performance. The implemented system comprises dual OL and SRL mechanisms. It comprises creating and externalizing goals, organizing learning tactics, and studying time. The classroom-based study included pre- and post-tests. After each lecture, students were informed about the weekly online examinations. Before weekly assessments, students took a conventional exam, and following online instruction, they took another post-test. The experimental results showed that there is no clear link between OL and SRL. Students who use SRL have good learning performance.

Furthermore, 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[6]. 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 [3] has made with 3 sectors covering behavioral, cognitive and emotional engagement.

Moreover, according to a review article which is referenced at [4] done by David Bueno, there are three main contributing factors that are influence to the satisfactory level of online education. They are, "Online Learner Factors", "Online Instructor Factors" and "Online Platform Factors". Under the online learner factors, gender, age, self-efficiency and health conditions can be highlighted.

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 optimise the SRL. The approach presented here will help to overcome the above barrier by personalising the SRL contributing factors.

In 2007, Feng-jung Liu and Bai-jiun Shih proposed a novel approach for learning material recommendation for e-learning courseware platforms to address, difficulty of learning resource sharing, high redundancy of learning materials, and lack of course briefs as three main highlighted issues.This study addresses these problems through two aspects. It was used 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 was used for identifying the keywords that were used in searching the materials and their relationship with those materials and collaborative filtering was employed in correctly filtering 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[8].

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.Also, this solution possesses the ability to integrate with different LMS's and they have designed a material registration interface to cater that facility. 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[10]. 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.

By paying attention towards all the approaches recommendation discussed above, it can identify the all of above end By paying attention to all the approaches discussed here, it reveals that all of the above end-products have been aimed at delivering a product that act as a standalone recommendation algorithm which improves the efficiency of recommending learning materials by being a part of search engine integrated ta given LMS. Although some of the above approaches have paid attention to both implicit and explicit attributes of the content to be recommended, none of them were personalized to suit for a specific LMS which are having their own syllabuses to be taught. Therefore, there is a high need for a recommendation approach which personalized to different syllabuses (Learning content) used in different institutes and behaves as an integrated recommendation approach to a LMS beyond a traditional recommendation approach in a search engine.

Furthermore, number of research has been conducted focusing on career path identification and career guidance. Vignesh S, Shivani Priyanka and Shree Mangju have come up with a career guidance system for the engineering students based on the their skills [14]. 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 engineer- ing) 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, [9] 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. A study in 2022 came up with an intelligent decision support system using the decision tree algorithm. [12] 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. [11] Recommendations have been given by calculating the similarity between candidate skills and the required skill set. By examining existing career guidance systems, the student skill identification phase is usually performed by analyzing student academic data. When the student grades are evaluated module-wise, in most cases it won't able to get accurate details on individual skills of the student.Also none of the above mentioned studies haven't considered all three factors of student technical skills, personal skills and the personal interest of the student simultaneously while identifying the career path. To fill the aforementioned gaps, this study proposes a machine learning approach based on the identification of the student skills and the IT industry-specific requirements.

According to the Lim Pek Choo and Jane Labadin in their study on student performance and forecasting [2], accuracy of the projected baseline grading is considerably higher when considering accuracy of the both standard grading and the projected baseline grading.

Student achievement in an online course is linked to their previous session performance as well as their level of interest. Literature has paid little attention to determining whether student performance and participation in previous tests may influence student accomplishment in subsequent examinations. So that, considering the above scenario, the requirement for the relevant solution is more confirmed. Researchers have done many case studies on the mentioned main objective performance progress analysis and forecasting as well as on career recommendations. Considering the conclusions and the methodologies of the [1], [7] and the [2], they have followed some basic methods such as,

- Student's exam marks analysis
- Graph theory to check the relationship between student and subject

Moreover, considering the existing real-world applications such as Blackboard, Jotform also has some features like result analysis as well as progress analysis. But they are more focused on the content delivered to the students. The following table contains the comparison between those existing applications with the proposed solution. Since this case study is mainly focused on how to personalize and optimize the learning strategies of students to provide a better online educational experience and align them with the up-to-date cooperation standards, the entire case study has been conducted as 4 main sub-case studies. Initially, the study was more focused on, how to identify and optimize the learning strategies of the student. Then, the study will slightly shift towards the techniques of increasing engagement in online education. Later, the case study will focus on how to effectively apply the online assessment protocols to achieve high accuracy in student analysis. This includes analysis of student performance and aligning their learning curve with current industry best practices.

III. METHODOLOGY

A. Identifying and Optimising the learning strategies

This case study proposes the Dynamic Weighted Probability Allocation (DWPA) approach to detect and assign possibility elements to each learning strategy. The new DWPA algorithm determines weights for weighted functions using logistic regression and weighted arithmetic mean. The newly developed algorithm will consider students' health issues, such as hearing and vision issues, while determining weight elements. It also focused on the learner's device for accessing instructional information. The key characteristics have been identified among the features mentioned in Section 2 with the help of the "hyper-parameter tuning" concept. Based on their health and other factors, each student is given a unique weight factor.

1) Data Collection: Since the new DWPA algorithm is based on logistic regression, 388 students were surveyed online using Google forms. The sample consisted mainly of college students (95 percent) and teenagers (15-19). The sample includes 99 percent distant learners and 1 percent hybrid learners. The same sample was used to recommend learning materials. For the "learning material identification and recommendation" phase, first- and second-year module outline documents from the Sri Lanka Institute of Information Technology were used to create a data collection with distinct learning contexts.

2) Process Followed: Before diving into the creation of the hypothesis function, the hyper-parameter tuning process was done in order to identify the contributing parameters. In the data collection phase, the audience was asked several questions to clearly identify the factors they were most concerned about in online learning and the usage of supportive learning materials.

Furthermore, 3 main learning strategies have been identified as audio, video, and text. It can be concluded that all the supportive materials that the students are using fall under these three main strategies. Therefore, the case study has mainly focused on categorizing and optimizing each student's learning curve in alignment with the above three main strategies.

In addition to the above, it was identified that the compatibility of adoption to the online learning of students has been limited to a few of the other parameters as well. According to the survey results and the information gathered from the literature survey, the age, gender, Specific health conditions related to learning, and Device type - D were identified as contributing factors to having a smooth online learning experience.

From the survey feedback, it was identified that a considerable number of students have hearing (H), vision (V), and focus-related health issues(F). Therefore, specific health conditions have been further divided into the above subsections.

With the identification of the contributing factors, with the help of the "hyper-parameter optimization" technique, the above factors have been narrowed down to have a fine-grained hypothesis function. The hyper-parameter tuning phase concluded that the aforementioned health conditions and the device type have a higher impact on the final probability factor. Therefore, the newly introduced DWPA algorithm is based on a linear polynomial function with these 4 distinct parameters(H, V, F, and D). Below is the primary arithmetic equation which is used to generate the probability weight of a given learning strategy. It is also the core hypothesis function that is used to calculate the probability weights of a given learning strategy.

$$P(\alpha) = (H(\alpha)\theta^h + V(\alpha)\theta^v + F(\alpha)\theta^f + D(\alpha)\theta^d) / \sum_{i=h}^{d} \theta_i \quad (1)$$

Here the α value represents the the 3 learning strategies namely video, audio and text.

But, given the fact that the P(α) value should a probability value and it should lie between 0 and 1, the aforementioned equation is being converted into a **sigmoid** function. This is where the principals of logistic regression is used in the DWPA algorithm. After the transformation of the above hypothesis function, below is the simplified version of the final equation.

$$1/(1 + e^{P(\alpha)})$$

$$= 1/(1+e^{P(\alpha)=(H(\alpha)\theta^h + V(\alpha)\theta^v + F(\alpha)\theta^f + D(\alpha)\theta^d)/\sum_{i=h}^{d} \theta_i}) \quad (2)$$

Here, in order to find the best values for θ, **gradient descendent** method has been used. With the help of multivariate gradient descendent, the function will converge into the best possible θ values. Since there is a requirement to fine-tune the weight factors (θ) values of the student, the proposed algorithm will re-run the workflow with the updated values for H, V, F and D.

3) Workflow Accuracy and Justifications: Focusing of the accuracy of the workflow, it has been optimised with the help of multivariate gradient decedent algorithm. The proposed model have the average accuracy rate of **78.86**%. The motivation behind the workflow is to fine-tune the assigned learning strategy's probability weights each after the student is assigned with new H, V, F, D values. Therefore, the model will explore unique ways of reaching the global optima of the given data set. Furthermore, since the proposed core equations is based on weighted average principals, the error impact on a given scenario will be minimized.

B. Personalized Learning Material Recommendation

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.

To introduce the context-specificity for learning material recommendations, it uses data-sets 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.

C. Career Path Identification and Job Opportunity Recommendation

This component is made up of two main sub modules.

- Career path identification
- Career opportunities recommendation

1) Career Path identification: In the implementation of this model, SVM with an RBF kernel has been used by following a multi class classification approach to classify the students into most suitable career path.

The student profile is maintained by the system under four aspects. Technical skills and personal skills which are identified by the examination module, skills determined by the student and the student career-related personal interests. Those prepared profile data has been used as the input for the above classification model. The following table showcases an example of a prepared student profile by the system.

Identified Technical Skills	JavaScript, Java, jQuery, React, Node JS, MongoDB, MySql, Django, AWS, Docker, Flutter, Git, Python
Personal Skills	Problem solving, Analytical, Creative thinking
Personal Interest	AI, Machine learning
Technical skills declared by the student	Azure, Datagran

2) 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.

- Intern/Trainee - Entry level
- Associate or 1-5 years exp - Mid level
- Senior/Lead or 5 years $>$ exp - Senior level

The system was designed to recommend jobs that have similarities of 50% or above. A student's skill set is defined by combining the identified skills and the defined skills by the student. Available job opportunities will be manually added to the system and required skills will be extracted. The similarity between the skills extracted from the job posting and the student skill set will be calculated using the Jaccard similarity index.

3) Data Collection and Preparation: Data set was prepared with the latest job postings related to the IT industry and skills were extracted using keyword extraction techniques. The data collected was organized as required skills along with the career path. Data was converted to a normalized tf-idf representation using TfidfTransformer.

D. Analyzing the Student Performance, Forecasting and Reporting

When it comes to the student performance analysis section, there are several phases of the methodology used throughout the project development, which are as follows,

- Problem understanding and data understanding
- System analysis and design
- Implementation and testing

1) 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 is established prior to system development in order 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 flows like,

- Quizzes for the first seven weeks which gives a discrete value for each.
- Mid-term Examination which gives both discrete and a grade value
- Quizzes for the last six weeks which gives a discrete value for each.

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

2) 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 diagram 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.

3) Implementation and testing: In order to produce IF-THEN rules for the prediction of students' results in the course ”Software Process Modeling” a data-set of almost 500 student records from the course is gathered and evaluated throughout the implementation phase using data mining techniques. 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.

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. 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 aforementioned 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, and presenting the detailed report.

IV. Conclusion

With the drastic movement towards online education, most students and tutors have started to face difficulties with productivity and engagement. With reference to the previous case studies and the online survey done in this case study, it was identified that personalizing and recommending the SRL boosts the engagement and productivity of education. Further, this case study demonstrates that each and every student has a unique learning curve and, in order to boost the efficiency of education, it should be personalised. Switching from in-class to online education has a vast range of benefits. Nevertheless, to achieve quality over quantity, required modifications should be made to the current LMS/CMS systems. With that being in mind, this case study proposes an all-in-one LMS which acts as a mediator between student and tutor. The application is solely responsible for personalising and optimising the students' SRL methods, analysing their performance, and keeping them updated with current industry trends.This application newly introduces few new personalizing techniques where none of the previously mentioned application have. Further, it includes fine-tuned mechanism to monitor student's personal performance in more statistic manner. Finally, with the in-built career recommendation feature, the users of this application get the benefit of orchestrating their learning with the current industry trends. With all above being said, the newly proposed application, collectively addresses all the research problems, discussed in the aforementioned sections.

References

[1] Raghad Alshabandar et al. “Students performance prediction in online courses using machine learning algorithms”. In: *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE. 2020, pp. 1–7.

[2] Lim Pek Choo and Jane Labadin. “Generating grade baseline marks for forcasting students' performance in Lower Secondary Assessment (PMR)”. In: *2011 7th International Conference on Information Technology in Asia*. IEEE. 2011, pp. 1–6.

[3] Mohamed Elmaadaway. “The effects of a flipped classroom approach on class engagement and skill performance in a Blackboard course: Effects of the flipped classroom approach”. In: *British Journal of Educational Technology* 49 (Mar. 2017). DOI: 10.1111/bjet.12553.

[4] *Frontiers — Factors Influencing Online Learning Satisfaction*.

[5] Rafael Glauber, Angelo Loula, and Joao B Rocha-Junior. “A mixed hybrid recommender system for given names”. In: *ECML PKDD Discovery Challenge* (2013), p. 25.

[6] Jim B.J. Huang et al. “Exploring Learning Strategies by Sequence Clustering and Analysing their Correlation with Student's Engagement and Learning Outcome”. In: *2021 International Conference on Advanced Learning Technologies (ICALT)*. ISSN: 2161-377X. July 2021, pp. 360–362. DOI: 10.1109/ICALT52272.2021.00115.

[7] Veenita Kunwar et al. "Chronic Kidney Disease analysis using data mining classification techniques". In: *2016 6th International Conference-Cloud System and Big Data Engineering (Confluence)*. IEEE. 2016, pp. 300–305.

[8] Feng-jung Liu and Bai-jiun Shih. "Learning activity-based e-learning material recommendation system". In: *Ninth IEEE International Symposium on Multimedia Workshops (ISMW 2007)*. IEEE. 2007, pp. 343–348.

[9] Tajul Rosli Razak et al. "Career path recommendation system for UiTM Perlis students using fuzzy logic". en. In: *2014 5th International Conference on Intelligent and Advanced Systems (ICIAS)*. Kuala Lumpur, Malaysia: IEEE, June 2014, pp. 1–5. ISBN: 978-1-4799-4653-2 978-1-4799-4654-9. DOI: 10.1109/ICIAS.2014.6869553.

[10] Mojtaba Salehi, Isa Nakhai Kmalabadi, and Mohammad Bagher Ghaznavi Ghoushchi. "A new recommendation approach based on implicit attributes of learning material". In: *Ieri Procedia* 2 (2012), pp. 571–576.

[11] Razkeen Shaikh et al. "An Intelligent framework for E-Recruitment System Based on Text Categorization and Semantic Analysis". en. In: *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*. Coimbatore, India: IEEE, Sept. 2021, pp. 1076–1080. ISBN: 978-1-66543-877-3. DOI: 10.1109/ICIRCA51532.2021.9544102.

[12] Ashutosh Shankhdhar et al. "Intelligent Decision Support System Using Decision Tree Method for Student Career". en. In: *2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC)*. Mathura, Uttar Pradesh, India: IEEE, Feb. 2020, pp. 140–142. ISBN: 978-1-72816-575-2. DOI: 10.1109/PARC49193.2020.246974.

[13] Yang Tzu-Chi. "Impacts of Observational Learning and Self-regulated Learning Mechanisms on Online Learning Performance: A Case Study on High School Mathematics Course". In: *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)*. Tartu, Estonia: IEEE, July 2020, pp. 194–197. ISBN: 978-1-72816-090-0. DOI: 10.1109/ICALT49669.2020.00063.

[14] S Vignesh et al. "An Intelligent Career Guidance System using Machine Learning". en. In: *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*. Coimbatore, India: IEEE, Mar. 2021, pp. 987–990. ISBN: 978-1-66540-520-1 978-1-66540-521-8. DOI: 10.1109/ICACCS51430.2021.9441978.