Learners' Preference Based Personalized Learning Material Recommendation System for E-Learning Platforms

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***Abstract*—This paper focuses on addressing the personalization problem of E-Learning platforms by building up a learning material recommendation mechanism based on the personalized characteristics and personal preferences of learners in the education context. This study introduces a way of identifying the relationship between the personal preferences/ personal learning style of learners and related learning materials. In achieving this objective, it will basically rely on the machine learning disciplines such as "Collaborative Filtering" which can be used to measure the relationship between learners' personal preferences with learning materials.**

***Index Terms*—E-Learning, Personalization, Learning style, Collaborative Filtering**

I. Introduction

According to Sujit Kumar, Marguerite Wotto and Paul Be´langer, the term E-learning refers to the use of internet technologies that are capable of providing a wide range of solutions to enhance knowledge and performance [1]. Although the E-learning technologies were evolved over decades, with the outbreak of the Covid-19 virus, the demand for the E-learning technologies was suddenly increased, since most of the education institutes were migrated from traditional methods of education towards the E-learning technologies [2].In addition, students process their own learning styles which define how the learner acquires the knowledge effectively while learning [3].These learning styles are reflected through the different behaviors and qualities of learners such as time spends on learning materials, types of learning materials referring, learners' personal preference towards a context, etc.

With the outbreak of the Covid-19 virus, since lockdown and social distancing has been taken as prevention measures spread of Covid-19, it was caused to shut down the conventional classroom education and hence most of these educational institutes had to move towards fully digitalized learning and teaching methodologies [2].With that sudden transformation, the quality and productivity of fully digitalized E-Learning were highly discussed and due to the lack of technical maturity of the existing E-Learning platforms, most of their defects and drawbacks were highlighted.

A major drawback that was highly marked was the personalization problem of the existing E-Learning platforms [4]. Not only in the E-Learning context, but even in the typical classroom education also, personalization was one of the major challenges since, in the conventional classroom education system, one teacher has to teach many students at the same time, and there, they use the same learning content, same teaching technique, same learning materials and a same teaching model for each student in the classroom [5]. This approach is widely known as the "one size fits all approach". In 1991, Cooper and miller claims that the accordance between the teaching style with the learning style of a particular student relates towards the performance and progress of that student. Through the conventional classroom educational approach, it is difficult for a teacher to figure out the most appropriate learning pattern of a learner. Even a teacher was able to identify the personal learning style of a learner it is much hard to adjust his/her learning pattern according to each and every learner in the class [5].
In contrast to the classroom education, E-learning offers a flexibility to teach each individual student in a way that most personalized to their learning pattern.Since through a web application, it is possible to gather multiple learning materials that fits for different types of learning styles and then recommend learners, the most appropriate learning materials

that aligns with their learning style.In a such system, in making recommendations, there are two preliminary considerations to be considered while making accurate recommendations. Those are,

- Intended learning context to be taught.
- Personal preference/Learning style of the learner

In consequence, the initial part of this study 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.

As a consequence of the above approach, by becoming input for the recommendation model, predictions of the key learning area directly affect the accuracy of the learning material recommendation model. To mitigate the effect of key learning area recommendations towards the result of the learning material recommendation model, it has been introduced a human interaction phase to correct the recommendations of learning area recommendations before feeding into the second phase. In this intermediate phase, the tutors are given the opportunity to make alterations to the initial learning area recommendations by adding, modifying, and removing initially recommended values. Through this approach, it ensures that the learning material recommendation model has a minimal effect on its operations by its key learning area related inputs.

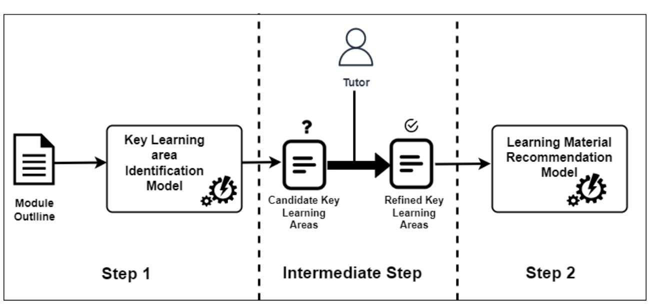

Fig. 1. Three Stages of Learning material Recommendations.

II. Literature Review

Making most accurate Recommendations will enable the students to learn the target subject area in a more efficacious manner and in a memorable nature. Furthermore, material recommendation prominently affects with the student's tendency towards a given subject area. The main objective of designing and implementing a learning material recommendation feature is to improve the progress and effectiveness of the students in a digitized learning environment, by recommending them with the learning materials that harmonise with their learning pattern and the learning preferences.

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

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

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

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

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

In the discussion of learning material recommendation, it is not vice to only rely on the literature of similar learning material recommendation systems, hence there are very powerful and accurate recommendation techniques and algorithms are already using in other contexts such as

E-Commerce. Thus, in the initial part of this literature review it will review some of common recommendation approaches and practices using appropriate research papers and then at the latter part this review will draw the attention towards more domain specific recommendation approaches based on some already purposed solutions.

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.

III. Methodology

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