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A Systematic Review on Recommender Systems for E-Learning in Post-Covid Era: Challenges and Research Opportunities

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***Abstract*— Online learning or E-learning evolved decades ago. However, online learning has increased significantly as the COVID-19 pandemic has spread. The education industry, too, suffered when the pandemic hit every aspect of everyone's life. Online education is becoming increasingly popular as a substitute for in-person teaching-learning to address the issue of learners not having access to classroom education. In a short time, all traditional classroom techniques are switched to online ones. Online education offers students a wide selection of courses and study resources. Recommendation algorithms take part a vital responsibility in suggesting relevant courses and learning materials for a specific learner from the vast amount of dynamically updating data available online. The purpose of this study is to give a thorough review of various E-learning Recommendation Systems and to discuss their recommendation mechanism. The study is mainly focused on the research conducted in the Post-Covid era. This article analyses several tools and techniques for recommending personalized learning in various E-learning systems. In addition, a discussion of the challenges of online learning recommendation algorithms and the future research scope will be included.**

***Keywords*— Recommender System, E-Learning, Filtering**

I. Introduction

With the rise of the COVID-19 epidemic, the significance of online education has become more prevalent since 2020. During the crisis, most countries were forced to go into total lockdown, imposing stringent mobility restrictions and ordering educational institutions to shift from traditional classroom instruction to virtual classroom mode.

There were many difficulties with teaching and learning then because of the instructors' inexperience and the learners' need for more awareness regarding online platforms. At that time, more online courses were introduced. It is essential to understand a learner's preferences for choosing courses, as well as their skills and the curriculum, before offering a course to that learner. A paradigm in e-learning called the "Personalized Learning Environment" (PLE) allows users to customize both the technique and the content of their learning environment. However, there are significant problems with PLE application in E-learning due to the abundance of information and the difficulty in finding appropriate learning materials for learners [1]. Therefore, choosing and delivering appropriate content for appropriate learners demands the use of recommendation algorithms. Due to two key factors—the increasing demand for individualized instruction and the accessibility of big data in the educational space—the recommender system has drawn the attention of research communities in education.

II. RECOMMENDER SYSTEM TECHNIQUES

Every recommendation system employs one or more strategies for filtering the suggestions, including Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic Filtering (DF), Knowledge-Based Filtering (KBF), etc., described below [2]:

Content-Based Filtering: In content-based filtering, the learner's preferences and learning interests are taken from their user profile. The recommender system should know the common characteristics among the learning objects that the user has previously reviewed and rated. The filtering algorithm suggests learning objects highly similar to the user's interests and tastes. For Newly added learning materials, CBF suffers from the cold-start problem. [3] [4] [5] [6]

Collaborative Filtering: The fundamental tenet of CF is that individuals with similar tastes will continue to share those same preferences in future too. This approach marks interest commonalities across groups of users using ratings or other user-generated feedback, and then it provides suggestions based on inter-user similarities [2] [4] [1] [7]. Like CBF, CF recommenders too suffer from the cold-start problem for new users.

Demographic Filtering: The user's demographic information, including gender, age, and date of birth, is used by a demographic approach to create recommendations. It divides the users into categories according to their demographic attributes. [3] [4] [8]

Due to the fact that it doesn't use ratings or user comments to make suggestions, it doesn't experience a cold-start issue. However, it is now challenging to obtain the necessary amount of demographic data due to concerns about user privacy, which limits the use of DF. [2]

Knowledge-Based Filtering: It makes recommendations based on its reasoning about what satisfies the consumers' expectations using knowledge about users and learning objects. [2] [5] [9].

Hybrid Filtering: The hybrid filtering method combines many ways for making recommendations in order to enhance system optimization and address specific technical issues and limitations. The concept behind the hybrid filtering technique is to integrate the two approaches, which will result in recommendations that are better and more effective than those produced by a single algorithm because the advantages of the two approaches will be balanced out [10] [7].

III. REVIEW OF RELATED WORKS

The concept of recommender systems evolved decades ago. It was introduced in the field of E-Commerce and movie or music recommendation. It also is beneficial in the field of online education. As a result of the Covid-19 pandemic, it has become mandatory to turn to online learning and to use recommender systems in the context of e-learning has also become increasingly important. A number of studies in the field of E-learning recommender systems have been conducted recently in order to overcome the difficulties related to the implementation of such systems in the Post-Covid era.

An integrated system for filtering and recommending educational materials that combines user collaboration with rule-based filtering was proposed [11]. The user-collaborative filtering method is used in this study to predict the learning outcome of the targeted student of a specific course. To recommend appropriate learning materials to the targeted student, a set of decision rules is used in conjunction with the predicted learning outcome and a set of decision rules. According to the author, the suggested recommender system is capable of offering recommendations for new students in accordance with the initial context-specific data acquired and analysed during the online enrollment test. The system can prevent cold-start problems up to an extent.

An improved recommendation system called Adaptive Recommendation based on Online Learning Style (AROLS) was applied by [12] to develop a learning style model that reflects the distinctive characteristics of online learners. AROLS comprises adaptive learning resource design by analysing student behavioural information to create a learning style model that accurately reflects specific characteristics of online learners. Three steps were taken to get the desired result: (i) group learners into clusters based on their preferred online learning style, (ii) use Collaborative Filtering (CF) and association rule mining to extract preferences and behavioural blueprints of each cluster, and (iii) generate a set of personalized recommendations.

Personal Learning Environment (PLE) is a concept used in online learning that gives users choice over the technique and content of their learning environment. Using the Collaborative Filtering (CF) recommendation system to identify appropriate learning content to learners' requirements, a study by [1] promoted the concept of PLE distance education. The proposed model uses the well-known Mean Absolute Error (MAE) technique of the recommender system to compare the error value of the value that was predicted with the actual value determined by the user target.

It has suggested a useful hybrid optimization algorithm-based e-learning recommendation system for user preferences [13]. Deep recurrent neural network (DRNN) and the enhanced whale optimization (IWO) method were merged in order to develop the algorithm. DRNN is used to order the categories for e-learners. Depending on their interests, learners may acquire course recommendations from these online learner meetings. The learners' behaviour and preferences are evaluated by completing the mining of the arrangements regularly monitored by the IWO calculation.

Another study conducted by [14] constructed a hybrid recommendation technique that enables students to access the learning resources arranged in any suitable course. Students without prior programming experience are the target audience for the system. It primarily aims to offer practical and inspiring content to online learners based on their various circumstances, preferences, knowledge concepts, and other vital characteristics.

It has put forth a methodology for creating learning paths that are appropriate for students' preferences and skills [15]. They propose a model for generating learning paths that takes into account static and dynamic learner parameters. According to this strategy, learning resources are suggested to students depending on their learning preferences and potential for grasping the particular learning resource. Additionally, the model forecasts each student's learning time frame and anticipated score. The results of this study are compared to those from three other models, and the results show improved performance with an increase in average accuracy in learning path prediction according to anticipated learning time and anticipated score prediction. However, due to the slow progression in results, more studies are recommended on this model.

It has written a review of recommender systems in the context of e-learning that are based on deep learning [16]. In the context of an online education platform, deep learning-powered course recommendation algorithms are examined in this study. The discussion includes an overview of current deep learning course recommendation systems as well as an analysis of the benefits and drawbacks of the methods that are currently available for choosing course resources. With thorough explanations of how each element of the framework operates, a generic framework for developing course recommendation systems is presented. It also highlights some current issues with course recommendation systems for further study.

The cold-start problem, which is a serious problem with Recommender Systems for e-learning in the case of fresh learners, is one of the main obstacles for recommender systems. A study [17] focuses on fresh learner cold-start problems in E-learning Recommender Systems and recommendations according to updating information. It reveals the incapacity of existing systems, such as content-based, collaborative filtering-based and knowledge-based recommendations, to gather precise data about learner. To overcome these challenges, a model proposed and discussed based on a dynamic ontology which recommends appropriate courses to fresh online learners.

Research by [18] offers a context-aware Learning Objects (LO) recommender system for course designers to design customized courses utilizing machine learning and filters. The suggested technique will also assist the academic community in creating specific courses that satisfy requirements for higher education curricula while utilizing current LOs. In order to provide a ranked recommendation list for the simple creation of personalized courses, a contextual ranking of LOs is established. In addition to the collaborative filtering technique, a collection of semantically pertinent LOs are retrieved from diverse LO recommendations using the teachers' feedback score. Recall, accuracy, and F-measure, which are commonplace machine learning metrics, are used to evaluate this system. According to the findings of the authors of this study, the proposed technique had a 93% accuracy rate in their assessments.

A study conducted by [19] offers a systematic analysis of how recommendations for customized content filtering in the educational sector have been generated and evaluated. It also comes up with the question of the field's limitations and how to advance them. According to the research, recommender systems for teaching and learning support usually use hybrid methodologies. The researchers' findings have some limitations, including challenges in getting data for evaluations and a dearth of in-depth research into the effects of well-known problems in the field of recommendation systems.

[20] It has studied building personalized recommendation systems for e-learning for K-12 students. This study mainly focused on K-12 students to identify the learning needs and challenges during the Covid-19 pandemic. It evaluates the sudden change in the educational sector due to unexpected lockdown and flipped teaching learning style, i.e. from traditional classroom learning to online mode. The challenges faced during the pandemic time also were discussed. The work depicts the possibilities and opportunities of online learning to provide better education for learners. According to the study's findings, school children should be given personalized material recommendations using a conceptual framework. The framework operates in a partially automated mode, with some tasks requiring human involvement and others being carried out automatically.

IV. CHALLENGES WITH E-LEARNING RECOMMENDER SYSTEMS

A few challenges associated with E-learning recommender systems are noticed during the review process. The common challenges with E-learning recommender systems are listed below:

Changing learner preferences: Learner preferences and profiles are the primary foundation of the recommender system for online learning. One of the primary issues in the e-learning recommender system is changing student preferences because the learner's interest and preferences may change over time. [10]

Cold start: This trouble arises when a new learner or course/study material is included to the system. Without ratings or reviews, a novel course/study material cannot be recommended to learners at first. As a result, it is tough to foresee the learner preferences or interests, which results in less reliable recommendations. [21]
To solve the new user cold-start issue, another study suggests an ontology-based resource recommender system for e-learning [22]. Here, the characteristics of the learner and the learning resources are modelled using ontologies. Using collaborative and content-based filtering strategies, the recommendation model delivers the top N recommendations in accordance with learner ratings.

Scalability: The system requires more resources as a result of the expansion of students and learning resources in order to process information and provide recommendations [10]. Since user reviews and ratings generate a lot of dynamic data, the scalability of algorithms employing real-world datasets for the recommendation system is one of the critical problems. Advanced large-scale methods are required to address this issue**.**

Sparsity: It occurs when most learners need not to rate or review the courses or study materials they utilized, which causes the rating model to become very sparse and may cause data sparsity issues. Sparsity limits the possibility of identifying a group of learners with similar interests. [21]

User Privacy: Recommendation systems need users' personal information to perform better in personalized recommendation services. However, because of the problems with data privacy and security, many users would not prefer to provide their personal information to recommendation engines that have privacy problems. The recommendation systems must ensure user confidence in order to address this problem. [10]

Synonymy: When two or more names or lists of items with the same phrase or representation are used to refer to the same object, this is known as synonymy. In such situations, the recommendation system cannot determine if the terms indicate different or similar items. [10]

Long-term and short-term preferences of learners: The recommendation algorithm finds it challenging to offer a good course or learning material for a specific period of interest because of the learners' diverse interests. While some preferences may only last a short while, others may have long-term or lifelong interests.

Inter-disciplinary course recommendation: Another challenge E-learning recommendation systems face is inter-disciplinary course recommendation. It needs multi-level filtering and correlation to identify the matching with learner interests.

Shilling Attack: It occurs when a malevolent user hacks into a system and starts sending out fraudulent ratings on specific items in order to boost or lower their popularity [21].

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V. CONCLUSION AND FUTURE SCOPE

In e-learning, recommender systems are crucial for addressing the problem of overabundance of information and assisting learners in finding appropriate and helpful learning resources from the massive amount of online learning resources readily accessible via the internet. This study attempts to assess the E-learning recommender systems developed both during and after the pandemic. Also discussed various techniques used with recommender systems to filter relevant and valuable learning resources from big data available on the internet and to suggest it for the right learner by analyzing the preferences and interests of the learner. The challenges faced by E-learning recommender systems are also examined and listed. Future research will focus on overcoming the aforementioned difficulties and creating an E-learning recommender system having improved performance.

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