International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I4P218
Volume 71 Issue 4, 203-212, April 2023

Review Article

A Systematic Literature Review on the Implications of Educational Recommender System in Teaching Learning Environment

Neeti Pal[1], Omdev Dahiya[2]

[1]*School of Computer Applications, Lovely Professional University Punjab, India*
[2] *School of Computer Science and Engineering, Lovely Professional University Punjab, India*

[2]*Corresponding Author : Omdev.26990@lpu.co.in*

Received: 02 February 2023 Revised: 10 April 2023 Accepted: 21 April 2023 Published: 25 April 2023

Abstract *- The education sector has drastically changed from offline to online mode in the past few years. Educational data mining, learning analytics, and machine learning are the fields that continuously process, monitor, analyse, predict performances, and display learning outcomes. Selecting an appropriate course still is the biggest challenge for learners. Recommendations can improve the learning process of learners and enhance their performance by providing appropriate learning objects. Informal learning requires special attention to the applications of recommender systems, which can guide learners through learning paths to achieve specific knowledge. This paper is a systematic review of the study of recommendation systems. The purpose of this study is to find out all the existing recommender systems that support the teaching/learning environment, its various techniques/approaches for implementation, and evaluation measures for measuring the quality and accuracy of the recommendation framework. This SLR methodology gives an opportunity to develop novel recommender system techniques in order to enhance the learning process of learners by giving them relevant learning objects.*

Keywords *- Educational data mining, Learning analytics, Recommender systems, Course recommendations, Deep learning.*

1. Introduction

In this digital mode of education, Recommender systems have become an important tool for personalized content filtering not only for learners but also for educators. It leads to the emergence of various models and techniques. The main goal of the recommender system is to understand the user's needs and make predictions and help them to find the preferable items quickly.

1.1. Classification of Recommender Systems

Recommender Systems are mainly classified into four categories: collaborative, content-based recommender systems, knowledge-based recommender systems, and hybrid recommender approaches.

1.1.1. Collaborative Recommender System

These systems make recommendations based on target users' and other users' similarities. Clusters of users are created using the clustering method, and then the correlation with the target is used for finding the recommendations.

1.1.2. Content-based Recommender System

These recommender systems analyze the ratings done by users about content. The proposed items are highly correlated with the user's profile.

1.1.3. Knowledge-based Recommender System

These recommender systems make recommendations based on the user's specific queries, not their ratings. This is based on the explicit preferences of users.

1.1.4. Hybrid Approach

Hybrid recommender system recommends combining collaborative with content-based or knowledge-based approaches to increase recommendations' accuracy [1].

This SLR study is divided into four sections. The first section describes the complete search process of literature. Search string used for research and screening process. The next section illustrates three research questions based on which the literature review is carried out following the next section. After the literature review, the three research questions are explained in a detailed manner. Finally, the SLR study is concluded and identifies future research directions.

2. Search String and Screening process

Regarding the Search strategy for this study, the papers have been selected from Google Scholar, a digital repository for researchers. The terms "Educational Data Mining" and "Recommender systems" have been used initially. The time range is customized from 2008-2022(till date). The number of research articles obtained is 17,800, which is not a feasible option. Again, the time range is divided into three groups. The first group ranges from 2008-2012, the second group ranges from 2013-2017, and the third group ranges from 2018-2022. The search string is then elaborated with the related keywords and synonyms combined with the "AND" and "OR" operators. The second string which is used in research is ("Educational recommender system" OR "course recommendation"). The search result of this string contains 3,360 articles. The next string is ("Educational recommender system" OR "course recommendation" AND "Learning",) having results of 3,050 articles. Both string options are not feasible. The final string for research with a combination of AND, OR operators and keywords are as follows:

("Educational Recommender system" OR "Course Recommendation" AND "Learning" OR "Educational Data Mining" OR "Learning Analytics")

The output of the first string for the year (2008-2012, 2013-2017, 2018-2022) is 372, 536, and 1250 respectively. A total of 2158 research articles are obtained.

2.1. Screening Process

The selection of papers is based on the objective criteria and scope of SLR. Inclusion/Exclusion criteria are applied for selecting relevant papers. 40 papers have been screened for the study of this SLR methodology.

An inclusion criterion describes the accepted norms for papers. Under Inclusion criteria, Papers with a systematic review of existing ERS publications are selected. Full papers from scientific journals regarding the techniques applied in recommendation systems are screened. Papers are verified based on title, abstract, and keywords, and papers written in the English language are selected. Papers represent the development of the recommender system, its applications in the education domain that support teaching/learning activities, and its evaluation.

An exclusion criterion describes the norms of ejection. Under Exclusion criteria, in contrast to inclusion criteria, all papers that do not support inclusion criteria are excluded.

3. Research Questions

This section elaborated on SLR research questions regarding educational recommender systems. Three research questions will be considered for this study.

RQ1 Existing recommender systems that produce recommendations in teaching/learning environment.

RQ2 Different techniques/approaches applied in the recommender system for recommendations and its performance evaluation measures.

RQ3 Types of educational datasets are available for implementation and evaluation of EDM/LA and Educational recommendations.

4. Literature Review

In this section, the results of selected papers are presented. Each paper represents a distinct recommendation system, data selection, recommendation approaches/techniques, evaluation methods, and evaluated results. All this information determines the answers to research questions.

This study provides a detailed analysis of existing recommender systems and gives an overall framework for course recommendations. Recommendations are introduced in an e-learning environment. The main emphasis is multilayer perceptual machines, RNN, CNN, neural attention mechanisms, and deep reinforcement learning-based recommendations [2]. An application of topic modeling for analyzing students' interests and collaborative filtering for finding students' similarities for effective recommendation [3]. Another study combines CNN with negative sequence mining to obtain personalized course recommendations. The model provides a list of courses but also predicts the courses mostly misslected by the users [4]. The research summarizes the limitations and researches new trends in the existing ERs. How are the recommendations produced, presented, and evaluated? [5]. This study designed a recommendation model based on the K-nearest neighbor algorithm. It recommends the set of optimal courses by assuming that the student can pass, assuming a lower dropout rate [6]. This paper contributes a novel approach that ensures the equality of learning opportunities. The fairness metric monitors the equality of learning opportunities among learners [7].

Prediction of learners with a higher possibility of failure at the initial stages by determining effective machine learning algorithms [8]. The Fragmented recommendation for MOOCs Ecosystem (FReME) course recommendation framework for MOOCs platform for suggesting parts of coursed from multiple providers. It reduces the learner's knowledge gap by enhancing the interactions and optimizing the learning process [9]. This works on collaborative filtering resource recommendations algorithm for online learning in sports. The evaluated results show a higher success rate with an average precision value of 98.21%, and recall rate is 98.35%, and an average F1 value is 95.37% [10]. This work analyses the behavioral patterns of MOOC learners. It predicts early dropouts and provides future courses in which students show more interest and less quitting the course [11]. A Dynamic recommendation of filtered Los (DRFLO) recommendation framework which recommends a ranked list of semantically correct learning objects from heterogeneous Learning Objects Repositories (LORs) according to the learner's interest. The result achieves a 93% of accuracy rate [12]. This research recommends the learning resources to learners based on learners' abilities and needs by proposing a method based on deep factorization. The proposed model also got tested on two experimental data, student's learning outcomes and 5 groups of learning resource datasets of users [13]. This work presents a resource recommendation system by the combination of MLP, BiLSTM, and LSTM using the attention method focussing on the users' interests and preferences. The result shows a 0.96 accuracy rate [14]. It develops a course recommendation model to select an appropriate course for recommendations for next semester based on his current academic learning outcomes. Several data mining and learning analytics techniques have been applied to predict learning outcomes. Effectiveness of results presented with the help of collaborative filtering and matrix factorization [15]. This work proposes an elective course recommendation system based on past students' grades using a Python programming language. Logistic regression classifies whether the course would be good or bad [16]. This proposes a novel course recommendation framework named Dynamic Attention and hierarchical reinforcement learning (DARL), which improves the recommendations for users having diverse interests in many different courses. For tracking the different user preferences, DARL automatically updates the attention weight for the corresponding course and improves the model's adaptability. Experiments are carried out on two real-world MOOCs datasets [17]—a questions recommender system based on a Bayesian network and analyzed/designed in software engineering. Educators provide Question recommendations for future validations to tell how its saves time to obtain the solutions [18]. This work proposes recommendations based on the grades scores by semaphores. Model biased matrix factorization algorithm predicts semaphore's elective course grades. It also considers the deviation that occurred due to the low selection rate. Ofcourse, it will make the prediction more accurate [19]. The author proposes attention-based CNN for personalized course recommendations for MOOC learners. It combined an attention-based mechanism with CNN to predict learners' course scores by extracting users' features and course features and recommending top N courses [20]. This research considers the student dropout rate as an important concern in MOOCs. Decision-making criteria are used to identify the core factors and their correlations.

6 out of 12 generated factors directly influence the dropout rate; these are academic skills and abilities, prior experience, course design, feedback, social pressure, and social support [21]. It provides a detailed review of deep learning methods applied to educational data mining tasks [22]. This study proposes a deep learning model for personalized recommendations for online courses based on a standard scenario of deep reinforcement learning. The first layer contains the course attributes, and the second layer contains the learners' profiles with the minimum number of hidden layers. Data are collected from various e-learning platforms of real online learners [23]. It proposes a hybrid algorithm framework combined with association rule mining. This framework has been experimented with on three learning platforms, Moodle, BookRoll, and Mahara(M2B), to obtain results [24]. This gives a user modeling methodology-based framework named Interactive course recommendation (ICRF), which recommends the courses based on the user's interest. Interests can be generated directly through surveys and questionnaires.

The framework combines sampling and interest propagation algorithms to make this more cost-effective. Experiments have been performed on real MOOCs datasets [25]. This study presents the MCRS recommendation system and algorithm for the MOOC platform based on Hadoop. The association data mining by Spark and information is converted into MySQL via Sqoop, which makes retrieving course recommendations more efficient [26]. Research explores how argumentation-based recommendation techniques enhance the efficiency of recommender systems. These frameworks are implemented in the repositories of learning objects of Colombia to recommend learning resources based on users' preferences and need [27]. This study contributes a new collaborative recommender system based on association rule mining which recommends the courses to target students based on the similarities among users. The association rule is the main tool for recommendations, relatively high confidence, and matches provide better performance [28]. It provides methods for building course recommendation systems. Recommenders help the students in predicting their results early and selecting appropriate courses. The study also analyses the results and compares their performance by applying them to real datasets. This paper also proposes a recommendation framework and is evaluated on RMSE measures [29]. This work presents a systematic methodology for personalized course sequence recommendations without using contextual information.

Forward search backward induction algorithm is developed that selects optimal course sequences. Multi-armed bandit tools help to improve the timeliness for completion of the graduate course and increase the overall GPA of learners. Algorithms out forms on real word datasets [30]. This study integrates issues from Moodle, WEKA, and data mining research fields. This paper provides a course recommendation framework. The data has been collected from Moodle, and the WEKA data mining tool has been used for data mining. Apriori machine learning algorithm is applied to predict course selection [31]. Research suggests that grade is an important parameter for selecting an appropriate course selection. Hence rather than focus on particular subjects, the proposed framework predicts students' grades if they choose a particular subject. A collaborative filtering approach is implemented on a real dataset and performs accurately [32]. This proposes a novel e-learning framework that encourages peer learning and social learning among learners. The set of experiments shows accurate results when compared to other recommender systems [33]. This research introduces a hybrid approach of Artificial Neural networks and data mining techniques for course recommendations. Firstly, ANN is used to classify learners with related interests, and data mining techniques are used to determine the best learning path [34].

Table 1. Research outcomes of recommendation systems

References	Research Findings
[2]	This paper provides a detailed analysis of existing recommender systems. The main focus is on deep learning-based recommendations.
[3]	This study reviews the existing methods and their performance in recommendations. Topic modeling analyzed the student's interest in some courses—machine learning method used for classification.
[4]	This paper proposes a personalized course recommendation model using a deep convolutional neural network with a negative sequence. The result shows that the model achieves higher recommendations with a lower dropout rate.
[5]	This work aims to review the research opportunities on ERS topic systematically. It informs how recommendations are produced, presented, and evaluated.
[6]	A recommendation system based on the K-nearest neighbor algorithm recommends an optimal set of courses. It poses the hypothesis that students following recommendations should have a lower rate of dropping out.
[7]	This paper provides a formalization of educational principles that model recommendations learning properties and a novel fairness matric that combines them to monitor the equality of recommended learning opportunities among learners.
[8]	This paper proposed a new model to predict the final grade by taking mid-term grades as source data. The performances of RF, NN, SVM, LR, NB, and kNN algorithms are used and compared for predictions. The data set consists of 1854 students who took the Turkish language –I course at the state university of Turkish for the semester 2019-2020.
[9]	This paper proposes FReME, a recommendation system to suggest parts of courses from multiple providers.
[10]	This paper designs an accurate recommendation algorithm. The data layer stores the video in the database and transfers it into the processing layer. The processing layer uses collaborative filtering algorithms to formulate the results and then transfers them to the user display.
[11]	In this paper, an edX course is dedicated to students in different fields—the course run of 2019 with 2489 enrolled users. Interaction with MOOC elements considers behavioral patterns and predicts early dropouts. The results are useful in designing future courses to engage more students with lower dropout rates.
[12]	This paper proposed a DRFLO recommender system that retrieves LO's from heterogeneous LOR's while designing a course.
[13]	This study presents a deep matrix decomposition model from Standard matrix decomposition to recommend learning resources based on learners' abilities and requirements.
[14]	This paper presents the resource recommender system as a combination of MLP, BiLSTM, and LSTM-improved deep learning methods. The proposed system provides higher accuracy.
[15]	This paper presents a recommendation system to select appropriate courses based on learners' academic performance. The results show that matrix factorization is the best choice for recommendations.
[16]	This paper proposes a Python-based course recommendation system using past students' grades. A logistic regression model is used to classify whether the particular course would be good or bad.
[17]	Since the user's preferences are dynamic, this paper proposes the DARL framework, which automatically captures the user's preferences in each interaction with the profile reviewer and recommendation model. Experiments have been performed on two real MOOCs datasets.
[18]	An academic question recommender based on a Bayesian network is developed for personalizing practicing by knowing the level of knowledge.
[19]	Proposed model biased factorization algorithm to find the prediction in score deviation due to course selection.
[20]	Attention-based CNN mechanism estimates the users' ratings and improves the relevance estimation, of course. This paper also proposed a framework to identify students' learning habits and assist them with preferred courses.

[21]	In this study, core factors and their correlations are identified using the decision-making method.
[22]	This paper identifies that deep learning techniques are beneficial for EDM tasks.
[23]	This paper proposed a recommendation system that suggests an appropriate course for learners based on their needs and profile.
[24]	This paper proposed a recommendation system based on association rule mining for the M2B hybrid learning environment.
[25]	This paper gives users an interest acquisition technology framework that queries directly about users' interests through surveys and questionnaires.
[26]	This paper makes course recommendations based on distributed association rule mining. The data is first pre-processed To make the course recommendations retrieval process more efficient and then converted into MySQL through Sqoop.
[27]	This work analyzed how arguments can help students to find appropriate learning objects for their profile and learning objectives.
[28]	This paper proposed a method based on a collaborative recommender approach that employs association rule mining to discover course patterns based on the affinity between the courses taken by the target student and other students.
[29]	This paper presents several methods for building a recommender system. K-nearest neighbors, collaborative filtering, matrix factorization, and biased matrix factorization can be used for predicting students' grades.
[30]	This paper presents a systematic methodology that recommends an optimal sequence of courses to minimize the graduation time and increase the GPA score of students with different contextual backgrounds.
[31]	This paper gives a framework for recommending the best combination of courses based on the learner's interest. Machine learning algorithms and association rule mining have been used to predict course selection.
[32]	This paper shows that the collaborative filtering approach gives students an accurate prediction of the grade they may get if they choose a particular subject.
[33]	This paper proposes a framework for a recommender system based on peer learning and social learning theories. The idea of recommending learning materials with similar content and learning quality can be indicated by good learner ratings.
[34]	This research constructs a hybrid system with an artificial neural network and data mining techniques. Integration of SOM and DM approaches constructs a recommendation system that helps e-learners to determine the optimal elective courses.

5. Research Questions Explanation

5.1 RQ1 Existing Recommender Systems that Produce Recommendations in the Teaching/Learning Environment

This paper proposes a recommender system that recommends resources based on the dataset of learners' interest, the time learners; spent on a particular resource, the number of clicks, etc. Then deep neural network techniques have been applied to obtain recommendations for learners' using educational networks [14]. This paper proposes a recommendation system that suggests an appropriate course for learners based on their needs and profile. These learners and profile parameters are fed to the learning model. These parameters can be improved by using learners' feedback [23].

A framework is proposed based on the LeCoRe approach, which combines Content-based and collaborative filtering in order to provide recommendations in accordance with learners; preferences. Preferences can be constructed on the learning history of past courses and learners' behavior from different platforms. REST-based web service is used as a platform to disclose recommendations. The services provided by this framework are limited to recommending learning content and finding a similar community of learners that encourages peer learning [35].

Web-based personalized recommendations framework for MOOCs platform learners. This framework recommends relevant courses to users based on their past ratings. Attention-based CNN identifies the learning habits of learners on the basis on which future estimation of relevant courses takes place [47].

A new approach named (New multi personalized recommender for e-learning) for e-learners. Personalization of learning materials according to learners' preferences, interests, and knowledge history of learners. The NPR-eL approach is based on content-based and collaborative filtering. The technique begins with two scenarios: determining the course content and the learning phase [37].

The research proposes an architecture for learners' annotation activities from different learning contexts, giving information on learners' characteristics. This information will act as input parameters for recommender systems for producing recommendations [38].

Content-based filtering, collaborative filtering, and hybrid filtering approaches are used in the proposed framework. This study mainly emphasizes hybridization, which improves the quality of recommendations. The research considers learners' choices and characteristics of learner resources, which in combination, are used for recommendations [45].

This study proposes a personalized framework for e-learners based on user information and content information. Data has been generated from user profile information and learners' behavior, and resource information database. This data generated the course choice list on which content-based and collaborative filtering techniques are used to generate recommendations [40].

Hybrid argument-based recommendation system for recommending learning objects. This system uses learners' information and metadata about the course content. Arguments are generated, and learning objects with higher argumentation is recommended by the system [41].

LSTM and RNN deep learning techniques are used to introduce a sequence-based course recommender framework. It recommends a sequence of courses based on historical course sequences to produce optimal recommendations [46].

5.2. RQ2 Different Techniques/Approaches Applied in the Recommender System for Recommendations and its Performance Evaluation Measures

This section provides a detailed view of machine learning techniques applied in recommender systems to produce appropriate recommendations. Moreover, quality measures are also an important factor in implementing these techniques in novel work. The following Table2: gives the detail of techniques and performance evaluation metrics.

Table 2. Various techniques/approaches and evaluation measures.

Authors	Techniques	Evaluation measures
[10]	Collaborative filtering	Recall, Precision, F1 value
[14]	Deep neural network, MLP. LSTM, BiLSTM.	Mean Absolute Loss, Root Mean Square Loss.
[20]	Attention-based convolutional neural network	Relevance Estimation
[23]	Deep Reinforcement Learning (Markov decision process)	Precision and Recall
[35]	Content-based recommendation Collaborative filtering	Mean Absolute Error (MAE) Root Mean Square Error (RMSE)
[37]	Collaborative and content-based filtering.	Precision, Recall, and F1 metrics.Pre-test scores.
[38]	Annotation-based technologies.	t-test, RMSE
[45]	Hybrid filtering Content-based and collaborative filtering	Precision, Recall, F-measure, ANOVA, T-test.
[40]	Content/collaborative filtering	MAE, precision, and Recall.
[41]	Hybridization (Content-based, collaborative, and knowledg based filtering)	Precision
[46]	Long Short-term memory (LSTM) Recurrent Neural Network	Create test cases on the pilot experimental group.
[43]	User-based collaborative filtering	Accuracy and Recall

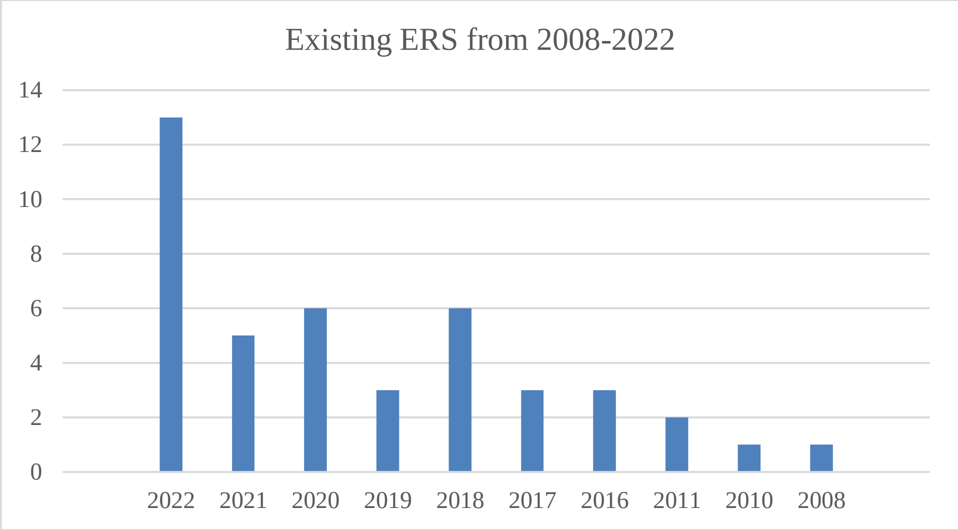

Fig. 1 Graph depicting the results for Research Question1

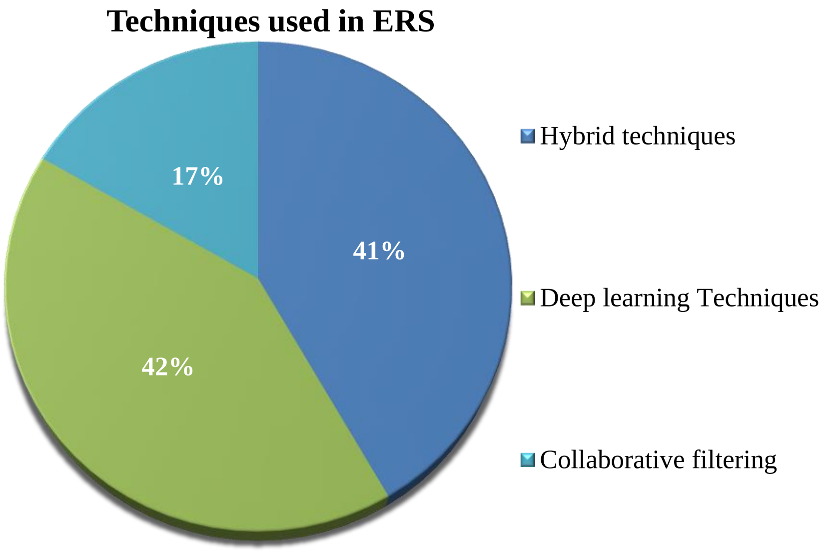

Fig. 2 Pie chart depicting the usage of approaches in Research question2

Table 3. Educational Dataset links

Author	Datasets
[14]	OULAD data sources
[22]	https://sites.google.com/site/assistmentsdata/ https://sites.google.com/site/assistmentsdata/home https://sites.google.com/view/edm-longitudinal-workshop/home https://www.knewton.com/ https://pslcdatashop.web.cmu.edu/ https://www.kaggle.com/aljarah/xAPI-Edu-Data
[23]	MOOCs, SPOC, SSOC data set of diverse e-learning platforms.
[35]	The dataset is collected from REST-based services and consists of 5000 unique learners and 49202 distinct courses—a total of 2,140,476 enrolments.
[37]	http://www.informatik.uni-reiburg.de/~ziegler/BX/
[45]	The experiment targeted two groups of students from public and private institutes. An online dataset has been usec
[40]	http://www.shlll.net/
[41]	FROAC: http://froac.manizales.unal.edu.co
[46]	10 years of university student transcript records.

5.3. RQ3 Type of the Educational Dataset Available for Implementing and Evaluating EDM/LA and Educational Recommendations

In order to perform recommendations and the evaluation of the educational recommendation system, there is a need for different types of educational data sets. All data sets are related to learners' behavior, learners' activities, learners' engagement with virtual learning platforms, and their learning path. Data sets are used as training and test data sets to implement and evaluate various machine-learning approaches. This section describes different types of educational datasets which are used for data collection, prediction, implementation, and evaluation of activities in a teaching/learning environment. Following are some links to educational datasets.

6. Conclusion

Digitalization of the education sector leads to the exposure of new ideas, approaches, and techniques that facilitate various teaching/learning activities and verify learning outcomes. Recommendation systems have gained attention in the education field in the past few years. This study will give a detailed view of existing educational recommender systems, which will contribute to developing novel recommender systems to enhance learners' academic performance and motivate them through personalised learning. This systematic literature review aims to analyze and compare all the existing ERs along with their implementation techniques and evaluation metrics. Evaluation measures will give future directions to researchers. All techniques are applied to particular datasets, and the performance of each technique is also determined.

In the end, researchers will be able to understand how recommender systems generate appropriate recommendations based on respective parameters. Deep learning techniques will enhance the quality of predicting behavior and generating relevant recommendations. Deep learning with educational data mining will enhance the potential of techniques and strengthen the recommender models which meet the educational need.

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