International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I5P126

Volume 73 Issue 5, 304-327, May 2025

Original Article

Advancing Educational Recommender Systems: An AI-Based Model for Personalized Learning Resource Recommendation

Neeti Pal[1], Omdev Dahiya[2*], Mrinalini Rana[3]

[1]*School of Computer Applications, Lovely Professional University, Punjab, India.*
[2,3]*School of Computer Science and Engineering, Lovely Professional University, Punjab, India.*

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

Received: 17 March 2025 Revised: 06 May 2025 Accepted: 19 May 2025 Published: 31 May 2025

Abstract - *A Recommender System can assist and guide the learners in selecting the learning resource that is coordinated to users' needs and preferences. Advanced learning methods provide various tools that increase learners' engagement and improve learning outcomes. This research work designs a collaborative filtering and content-based filtering recommender system for an educational environment. The personalized recommendations are made based on learners' interests in particular resources. By analyzing the Open University learning analytics dataset (OULAD), the relevant resources are suggested to learners by evaluating the number of clicks on the resources. A personalized recommender system contributes to understanding the concept of explainable Artificial Intelligence to make models more interpretable and rationalize their decisions. The evaluation results with an average accuracy of 0.9973 and Root Mean Squared Error (RMSE) of 0.0606 provide more appropriate recommendations compared to similar studies. Additionally, the model showed recall and precision values of 1.0, outperforming other existing methods. This recommendation model is highly adaptable and capable of integrating with various Learning Management Systems (LMS) in educational domains, thereby enriching students' learning experiences with finely tuned personalized suggestions.*

Keywords - *Collaborative filtering, Educational Recommender System (ERS), Higher Education, Resource Recommendation, Educational Data Mining, E-Learning, Learning Outcomes, Artificial Intelligence (AI), AI in Education (AIED), Interpretable Machine Learning.*

1. Introduction

The emergence of the Recommender System (RS) and methods in educational settings for recommending learning resources has gotten attention in the past few decades. Abundant courses and resources are available for E-learners in online learning environments. Election of suitable course material should meet the demand of learners' career choices and their learning path. The choice of relevant material is highly important for the successful completion of a particular course [1]. In traditional education settings, the teachers or mentors do the recommendation and mentoring part. Moreover, there were limited resources at that time. In the educational landscape, the implementation of RS has become increasingly crucial to enhance the learning experience. Designing an educational recommender system for an E-learning environment is quite an exigent and stimulating issue. Educational recommender system aims to provide the relevant course learning materials tailored to users' needs and interests, which ultimately increase the users' engagement levels. ERS highly affects the learning outcomes of learners by satisfying the different knowledge levels with diverse needs. Research shows the significant gain in the before and after the implications of educational recommender systems. The educational domain indeed holds great potential for enhancing the distribution of academic material to students. By analyzing students' learning styles, preferences, and past interactions with educational content, recommendation systems can personalize the learning experience for each individual [1]. Traditional one-size-fits-all approaches often struggle to address the diverse needs and learning styles of individual students. By leveraging machine learning (ML) algorithms, education systems can tailor learning experiences to better suit each student's preferences, pace, and proficiency. Overall, ML enables education systems to move beyond a one-size-fits-all approach, empowering educators and learners alike to create more personalized, effective, and engaging learning experiences [2]. Recommendations consider a variety of factors such as demographic characteristics, past preferences, item ratings, purchasing history, etc. These factors play a vital role in giving the precise recommendations. Nowadays, recommender systems are widely spread in the domain of education owing to the change in the learning styles of the learners. RSs play a crucial role in enhancing user experience, engagement, and satisfaction by helping users discover products and content that are most likely to meet their preferences and interests. By leveraging ML algorithms and user data, RS can provide tailored recommendations that improve decision-making and promote user loyalty and retention [3]. The methods that are used in recommender systems are based on various techniques. Recommender Systems are mainly classified into four categories: collaborative, content-based recommender systems, knowledge-based recommender systems, and hybrid recommender approaches. Learners may find it difficult to access the best course material from a lot of information due to their lack of expertise. The personalized RS addresses this issue and facilitates the relevant recommendations for online learners by considering various factors like learning styles, preferences, and adaptive levels [4].

Due to the advancement in virtual learning environments, high-quality online resources have been shared with users. ERS works according to users' interests and preferences and suggests the appropriate resources to the users [5]. RS recommends the optimal set of courses, which lowers the dropout risk by establishing less difference between the set of passed courses and the set of courses that are recommended [6]. It is very important to consider the learners' career decisions and other factors while suggesting the appropriate course materials from thousands of available courses. To address this issue, the Personalized RS arises with a solution that aims to match the preferences with the resources [7],[8]. Deep learning (DL) techniques give significant recommendations and provide outstanding results in different problems. The DL-based model has gained momentous growth [9]. Existing RS still faces problems that deal with cold start and data sparsity. Detailed information on users' profiles and behavior will improve the recommendation process.

Learning style, behavior patterns, and level of knowledge factors need to be considered to create accurate recommendations [10]. In an educational setting, an ERS sustains a learning object that is based on users' learning needs and preferences. A learning object is considered an entity in an educational setup that can be used, reused, and assists the learning path of learners [11]. RSs offer an alternative to human advisors [12]. Some traditional RSs recommend the material to users not only based on their interests and preferences but also by aligning the choices to earn more credits. Later on, users will find the course less interesting. The need for an effective communication environment between the users and intelligence will lead to capturing the preferences more interactively [13]. It is difficult for existing methods and techniques to cope with large amounts of educational data, so they need to benefit from ML algorithms and the structures of Artificial Neural Networks (ANN). Personalized recommendations will enhance the learning experience of learners. Providing the relevant learning material to the users according to their career decisions will make the learning journey more productive. It can only occur by knowing the users' learning styles, preferences, and learning patterns. The existing RSs suffer from different issues, such as a lack of users' information, learning patterns, users' interests, and preferences. Addressing cold-start problems in RSs, particularly for new students or resources with limited interaction data, is a significant challenge. The network settings with existing educational resources become outdated and unusable.

Due to the drastic changes in the educational environment, new scientific resources are constantly increasing. Educational resources are getting updated day by day. So, there is a need for a gradual change in the present network settings. Network learning should place emphasis on future resources rather than present resources to achieve accurate recommendation results. This requires a continuous and adaptive network setting environment to accommodate evolving resources. These issues comprise (a) incremental learning techniques that allow the models to continuously update with new information without complete retraining. Algorithms that can handle a large number of user-item interactions efficiently (b) Real-time RSs need efficient data structures and memory to handle multimedia sources and high-dimensional tensors [5]. Development of compression methods to reduce the high-dimensional input data without losing the information. Auto-encoder techniques and various data reduction algorithms need to be explored [5],[14]. Knowledge distillation algorithms are required to infer knowledge from a larger mentor model to train a smaller learner model is a critical task for real-time applications [5],[15].

A personalized recommender system will intensify the learners' interest in particular content and reduce the course dropout rate. The recommender system makes the decision-making process for choosing the appropriate content easy for learners.

The remainder of this article is categorized as follows: a detailed description of an ERS, along with a problem formulation description, is presented in the introduction section. Various types of ERS techniques are discussed in the related work section. A detailed methodology of the proposed framework is demonstrated in the methodology section. The evaluation of the results is presented in the next section. Finally, the results discussion and future work are presented in the last section.

1.1. Explainable Artificial Intelligence (XAI)

Artificial Intelligence (AI) is highly utilized in worldly applications, which enables evidence-informed decisions. To design an accurate AI model's enormous quantity of data is required. This data is highly complex and non-linear [16]. Researchers have worked on Deep Neural Networks (DNN) to extract the patterns from a highly complex dataset [17]. To make out the differences due to non-linear data filters and kernels are introduced to increase the performance of AI models. A Neural Network has several layers with many neurons and filters, and DNN subsequentially creates a complex network with several parameters and layers, which makes the network design more complex and less interpretable [18]. The complexity of neural network structural design depends upon various factors, number of layers, activation function, classifier methods, normalization technique, weight updating, and cost/ loss functions.

Due to this, unlike simple machine learning algorithms, it is difficult to make out of DNN models. This will lead to Black - Box Problem [19]. Simpler Machine learning (ML) models like Decision trees (DT) are easier to grasp and also interpretable, which gives the self-explanations for the models' decisions [20]. Fuzzy- Rule-based systems and Bayesian networks are called gray-box models, which are partially interpretable if designed carefully. There is also a concept of White- Box models, which can be easily understood by catching a glimpse of the parameters without needing any external model to explain [21],[22]. Thus, the black–box and gray-box models are neither self-explainable nor self-interpretable, whereas the white-box models are self-interpretable.

Moreover, the White – box designed models are highly explainable but have less accuracy in results due so they can't be used in daily applications. On the other hand, Gray- box models provide significant accuracy with explanation to some extent, and Black – box yield a good performance in terms of accuracy. Still, due to its non-explainable nature, practically, it can't be used in unfavorable applications. XAI focuses on making models more interpretable and rational for their decisions. XAI techniques play a vital role in explaining the non-biased decision-making mechanism of the model in making predictions and enhancing the transparency of the model by revealing the internal workings of the model [16]. In terms of interpretability, XAI in machine learning models can be defined as the extent to which humans can understand the reason for a decision and can understand what exactly the model does [23],[24].

1.2. Xai in Education

XAI techniques are applied to achieve trustworthy models where the outcomes of the models are comprehensible to humans. Earlier extensible Artificial Intelligence has been used in delicate domains like military, healthcare, and banking applications. XAI is an emerging technique that promotes transparency, explaining the reason behind the decision-making in the AI model. Artificial Intelligence in Education (AIED) makes the sophisticated use of AI in the learning experience, especially in personalized learning. XAI in education has diverse significance depending on the users (teachers, learners, or parents) and their specific tasks. For teachers, the point of view may be concerned about how to increase student engagement, student focus, individual monitoring, and guidance, reduce dropout rate, and selection of appropriate course material. Parents are more concerned with how they can help their children in learning, whether emotionally, financially, or physically. Learners are highly concerned with how they can enhance their learning outcomes and get good scores [23]. For effective educational outcomes, feedback plays a crucial role both for learners and teachers.

The purpose of feedback is for teachers to assess the effectiveness of teaching styles/ pedagogies, curriculum design, and teaching techniques. Common things that explicitly reflect the teaching are students' engagement, performance (grades), participation in activities, and teacher-parent coordination. Checking on these aspects allows the teachers for effective in teaching [25],[26]. Explanations provided by the teachers served as feedback for the students, such as learners' academic performance, guidance to improve, valuable comments, and positive motivation, which build self-confidence and self-esteem among learners [27]. The proposed work generates high-quality recommendations with the role of eXplainable AI to develop an interpretable and trustworthy model.

2. Literature Review

In this section, the existing ERS techniques that are reviewed for the research work are discussed. Emerging research indicates how RSs play a vital role in the learning journey of learners. The details of evaluation metrics, result outcomes, and future enhancements are also depicted in a tabular format for a better understanding. The research discusses the key features, functionalities, and applications of ERS in teaching and learning contexts. Categorize implications into positive effects and address issues such as algorithmic bias, data privacy concerns, scalability, and usability challenges. It explains the broader implications of ERS in shaping the future of teaching and learning in digital environments [3].

This research integrates a multi-agent approach and deep reinforcement learning to suggest top N courses in massive open online courses (MOOC) learning platforms by providing a personalized and adaptive model. The 100K Coursera reviews validate the performance of the model. The multi-agent DRL techniques approach dominates the single-agent approach and learns the dynamically changing users' preferences and tracks the changes in course contents. Feedback provided by the users will enhance the quality of recommendations [4]. Dynamic ERS recommends resources to the users based on the dynamic preferences and interests of the users. It considers users' long-term and short-term users' dynamic activities. The proposed model uses BiLSTM networks for appropriate recommendations with an average accuracy of 0.9978 [5].

A novel methodology for predicting the students' outcomes in terms of pass and fail categories. This system utilizes the academic, demographic, emotional, and VLE sequence information of students from the OULAD dataset and the emotional data that was originally generated for this study. RNN and LSTM are integrated with machine learning models to enhance the prediction of research. Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), and Naïve Bayes (NB) are used with RNN and LSTM. The result shows that RNN + LSTM + RF gives better results than integration with other models [28].

The analysis of the dataset from Kaggle compressed 1205 students from high school to college students and designed a hybrid model for online education to forecast the learners' adaptability levels in E-learning. Several machine learning models, like logistic regression, DT, KNN, and Ensemble ML models such as RF, ADABoost, and ANN, are used for predicting adaptability.

The proposed hybrid model achieved a high accuracy of 94.04% signifies the research outperforms in terms of performance metrics with this dataset than the other models [29]. An APP-DGNN model to predict the academic performance of learners is introduced. The key insights from this study included two modules: An interaction-based graph neural network (IGNN) and an attribute-based graph neural network (AGNN). IGNN comprises the student online interaction activities, and AGNN comprises the similarities and differences among the students. The representations from these two graphs are considered as local and global representations. The representation from local to global levels is combined to form a learning module to generate predictions regarding academic performance. Their proposed method outperforms with 83.96% accuracy in predicting the pass or fail student and 90.18% accuracy in predicting the pass and draw students [30].

An idea of adaptive learning combines DL for personalized recommendations and object-oriented features to build an object-oriented online course, RS. This methodology provides personalized recommendations according to the needs and preferences of individuals. The proposed system is evaluated with a real-world online course dataset, which results in an improvement in the online learning experience of learners. Their research emphasizes object-oriented features such as scalability and maintainability, which were overlooked earlier in the literature [31]. A resource recommendation model based on an adaptive genetic algorithm to address the challenge of information overload in online teaching resources [32].

The framework is named an Intelligent Content-Based RS framework that leverages semantic analysis and DL techniques to provide personalized recommendations of e-learning materials to learners. By incorporating contextual and semantic information, the framework enhances the relevance and effectiveness of recommendations, ultimately improving the learning experience for users. The models are evaluated and compared using a user-sequential semantic dataset.

The results indicate that the LSTMM model outperforms others in terms of accuracy and F1-score, achieving values of 0.8453 and 0.7731, respectively [33]. Building a recommendation system using DL techniques by knowing the user's preferences from features like comments, ratings, dislikes, and likes. The ResNet-152 approach has generated recommendations. The ShuffleNet V2 technique is used to predict the number of users with recommendations and without recommendations at the end. They modified the Butterfly algorithm to optimize the performance of the model [34].

By combining user-collaborative filtering with rule-based filtering, a system predicts a student's learning outcomes and recommends relevant learning materials accordingly. A key feature of this system is its ability to provide automated recommendations to new students based on initial contextual information collected during program entrance tests. Their research contributed to the ongoing exploration of RSS in education, offering insights into how personalized learning can be facilitated through data-driven approaches [35].

Development of a personalized online education platform that utilizes a collaborative filtering algorithm for recommendation purposes. The platform is designed to be cross-platform compatible using HTML5 and a high-performance framework hybrid programming approach. On the server side, the platform adopts a mature B/S (Browser/Server) architecture and follows a popular development model. Meanwhile, the mobile terminal employs HTML5 and a framework to implement personalized course recommendations using collaborative filtering and recommendation algorithms.

The online teaching on this platform offers a comprehensive approach to online education, combining personalized course recommendations with both asynchronous and synchronous learning modes to cater to different learning preferences and needs [36]. Findings from this study revealed the recommendation algorithm that integrates semantic information with a collaborative filtering algorithm. By calculating the semantic similarity between recommended items, the algorithm can identify courses that are closely related in terms of content, learning objectives, or educational level.

This helps ensure that the recommended courses are not only relevant to the learner's interests but also complementary to their existing knowledge and skills [37]. This study found an interesting link between ML techniques like MLP, BiLSTM, and LSTM with attention mechanisms to personalize recommendations in the field of education to address a crucial need for personalized resource recommendations based on both short-term and long-term user interests. The results achieve a high accuracy of 0.96 and a low loss of 0.0822, indicating the effectiveness of your approach compared to other methods [38]. The analysis showed that the model uses a two-step approach that combines unsupervised DL and deep auto-encoder techniques. Learner feature mining followed by clustering the learners into groups based on their learning styles using Kohonen maps. Deep auto-encoder transforms the representations to estimate the success rate of learning resources for the recommendation generation to learners [39]. Table 1 provides a detailed view of existing techniques of the ERS are organized in tabular form, which involves evaluation parameters, the research outcomes, and the future directions of the research. Future enhancements will give future directions to the researchers.

Table 1. Analysis of existing recommender system studies

Author	Publication Year	Evaluation Metrics	Research Outcomes	Future Outlook
[4]	2024	Recall, Precision, hit ratio, Normalized Discounted cumulative gain.	The proposed DRR model outperforms and has better recommendation generation.	The researcher aims to broaden this research by including multiple MOOC datasets consisting of the large number of learners and courses.
[5]	2024	Precision, Recall, F1-score	The proposed model supports dynamic learners' behavior. Appropriate recommendations are obtained with an average accuracy of 0.9978.	Work needs to be done in the network training process as the number of resources gradually increases; therefore, more networks need to be trained.
[33]	2023	Accuracy, Recall, Precision, F1-Score, and ROC curve	The proposed ICRS system guides the learners in the selection of appropriate e-learning resources by using users' sequential and semantic data.	Handles the challenges regarding the customization of the learning model. Generalization of the model to fit numerous cases on the web also needs to be implemented.
[38]	2022	Mean Absolute Loss, Root Mean Square Loss	The proposed system employs the resource recommender system, which recommends the resources by using LSTM, BiLSTM, MLP, and deep learning techniques in coordination with users' needs and interests.	Systems are more focused on the needs of learners rather than paying emphasis to assisting and supporting the teachers and decreasing their workload.
[40]	2022	Precision, Recall	The proposed model achieves higher personalized course recommendations with a lower retention rate by using a deep convolutional neural network with a negative sequence.	Significant work in predicting the mis-selected courses for recommendation, which gives new sagacity for course recommendations in E-Learning.
[41]	2022	Recall, Precision, F1-score	This paper gives precise recommendations for sports online learning resources. The processing layer uses collaborative filtering to meet the needs of different learners.	More work needs to be done to deal with cold start problems and data sparsity.
[42]	2018	MAE, Precision, and Recall	This paper suggests relevant learning courses in E-learning by using collaborative filtering, association rules, and content filtering.	Utilization of pilot recommender systems in open education to promote the learning volition of resources and increase the efficiency of recommendations.

[43]	2018	Mean Absolute Error (MAE) RMSE	LeCoRe: Hybrid recommendation framework to model the users' preferences by solving the cold start problems for the new ones.	Recommend the learning objects by the users' career choices and provide the most suitable path according to their interests.
[44]	2017	Precision, recall, and F1-score, Pre-test scores.	The proposed NPR_eL approach integrates preferences, background knowledge, and interests to support each learner's needs.	New educational recommender systems must ensure the personalization of learning content.
[45]	2011	Apriori Association rule	The proposed framework provides the best combination of courses by knowing the learning behavior of the learners and their interests.	With the combination of data mining algorithms. Obtain the best combination for the course selection.

3. Proposed Methodology

The proposed work will deliver a highly sophisticated RS for the educational domain. This framework will outline all phases of complete research work in well-defined steps. The research is highly inclusive and provides better insights for future work. The comprehensive methodology section has defined the different stages of research to accomplish the task.

Figure 1 illustrates the general workflow, which visually represents the comprehensive steps for the designing of an educational recommender system. The diagrammatic representation of the detailed workflow of the proposed methodology illustrates the steps, sequences, and processes to be followed for designing a resource recommender system.

Figure 2 represents the detailed workflow of the resource recommendation model, which means all the components from data input preparation to recommendation generation. Data acquisition and preprocessing are the phases that need to be fulfilled before building any model. The steps of data preprocessing are discussed in detail.

The Open University Learning Analytics Dataset is a publicly available, large-scale online learning environment dataset for academic research. It is widely used in the fields of learning analytics and educational data mining due to its authenticity. OULAD is a well-suited educational dataset for developing and evaluating an educational recommender system. It represents authentic student-resource interactions in the virtual learning environment. The dataset tracks the student performance and predicts the outcomes flawlessly.

OULAD sets a standard in academic research by allowing novel approach results to be compared with the existing ones for their efficiency, validation, trustworthiness and relevance.

The proposed work is evaluated with the OULAD dataset, consisting of 22 courses with 32,593 students, their assessments, demographic information, and aggregated sum clicks of interactions with resources in a Virtual Learning Environment.

Data enables the prediction of results and analysis of learners' behavior from interactions with resources. Log interactions with the virtual resources are represented by several clicks with 10,655,280 records [46]. The recommendation process in our system utilizes historical user interactions to predict the top resources (activity types) for each user within the virtual learning environment. Our final data frame contains 3 columns and 220,871 row(s). Figure 2 presents a detailed walkthrough of the steps followed in the proposed work.

The following figure 3 provides the four phases of the flow of the proposed methodology. The different phases for building a recommendation model are represented diagrammatically. The breakdown of each phase of the diagram is as follows.

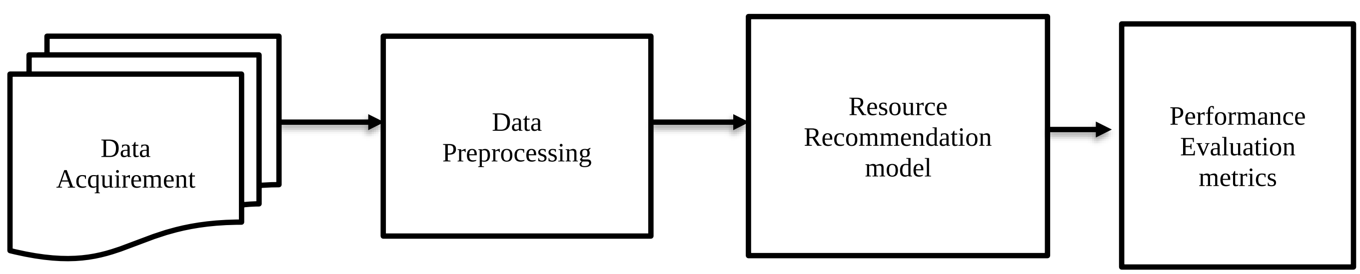


Fig. 1 General workflow

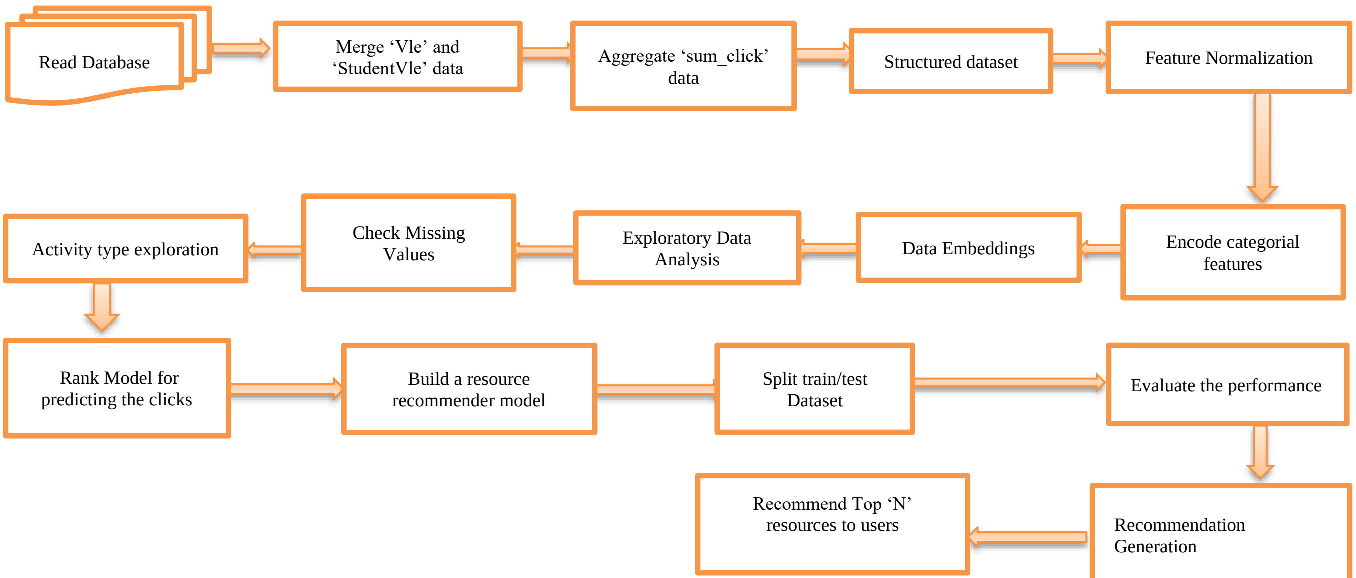


Fig. 2 Detailed flowchart of proposed work

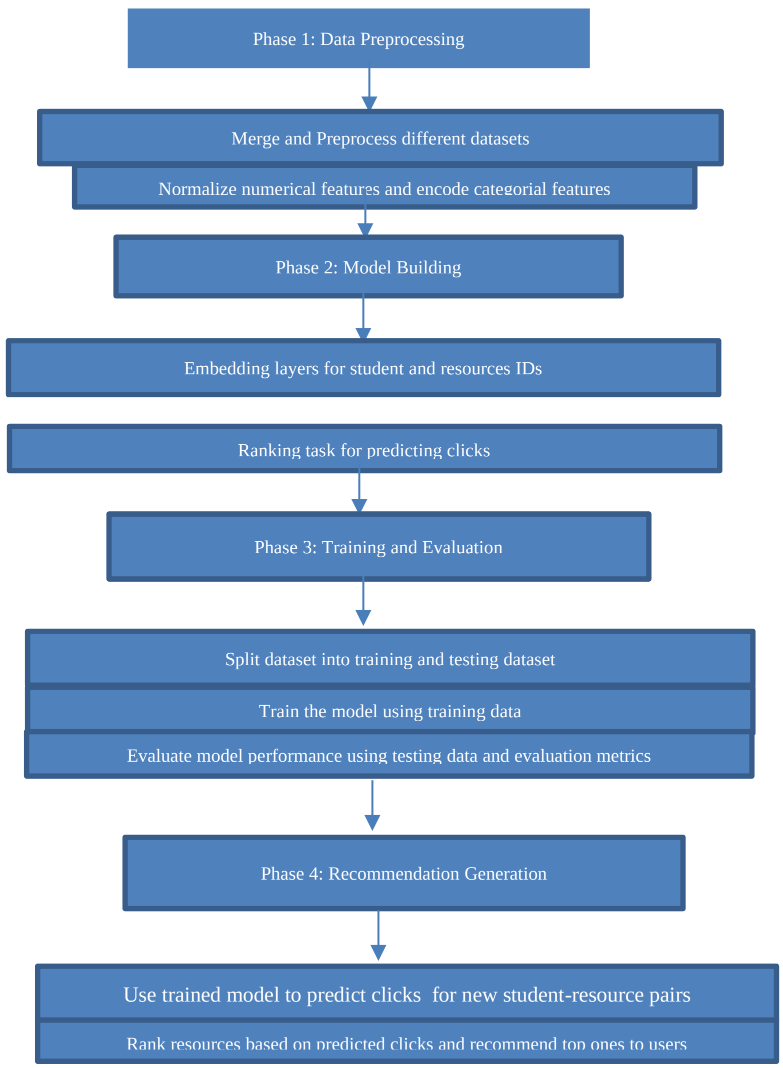


Fig. 3 Different phases of the recommendation model

Phase 1: Data Preprocessing

In this phase, two steps have been followed. Firstly, preprocessing and merging the different datasets to make a single dataset for further analysis. Normalize numerical features and encode categorical features to make the data an input to the model. Thus, the first phase cleans and preprocesses the data to ensure its quality and compatibility with the model.

Phase 2: Model Building

This phase builds a recommendation model using embedding and dense layers by capturing the interactions between the students and resources. These embeddings pass through different layers and define the ranking tasks by predicting the clicks modeling the students' engagement with each resource.

Phase 3: Training and Evaluation

The next phase is to train the model to know its effectiveness by splitting the datasets into training and testing datasets. Evaluate the performance of the model by using various performance evaluation metrics to determine the accuracy of the model.

Phase 4: Recommendation Generation

The final phase is to generate personalized recommendations based on the click predictions. Initially, the trained model will predict the clicks for new resource-student pairs and identify the resources that are mostly liked by the student. The next step is to rank the resources based on the click probabilities and recommend the top N resources to the users.

The following subpoints provide a detailed, step-by-step explanation of the process outlined in Figure 2.

3.1. Data Acquirement

The recommendation system is specifically tailored to utilize the OULAD. This dataset serves as a rich source of information, capturing various aspects of student interactions within virtual learning environments. By leveraging the recommendation system caters to educational institutions that prioritize data-driven approaches in augmenting their virtual learning environments. To facilitate the deployment of the recommendation system, it is imperative to acquire the OULAD [46]. The provided code streamlines this process by automating the download and extraction of the dataset. Local access to essential datasets, including student assessments, Virtual Learning Environment (VLE) data, courses, student information, and registrations, is essential for seamless operation. This database includes the students' data enrolled in multiple courses. It consists of students' demographic data, course enrollment data, and assessment data of 32,593 students. This dataset also stores the user-resource interaction log data in the virtual learning environment. The files which are used are briefly described below: The wget utility is utilized to download the dataset, followed by unzipping it into the current working directory for easy accessibility.

Vle.CSV: It contains information about the available resources in the virtual learning environment. These learning resources are in a PDF file or HTML format, etc. Students interact with these resources, and their interactions with items have been recorded.

Student Vle.CSV: It contains information about each user's interactions with the resources in VLE.

Student Info.CSV: It contains the demographic information of learners along with their results.

Before starting to build the model, there is a need to ensure the TensorFlow-recommenders package is installed. It will guide with full workflow starting from data preparation, model formulation, training, and evaluation.

3.2. Data Loading and Preprocessing

In the initial phase of data preprocessing, critical datasets, particularly 'vle' and 'studentVle' (student interactions with the VLE), are loaded and merged. Figure 3 represents the merging process that consolidates relevant information from these datasets into a structured dataset, facilitating future analysis and model training tasks. The Pandas library is employed for this purpose, leveraging its functionality to efficiently handle and manipulate tabular data. To commence work with the dataset for the RS, it is essential to download and extract the necessary data. The provided commands automate this process, ensuring that the dataset is readily available for subsequent preprocessing steps.

Following the dataset acquisition, essential libraries are imported, and warnings are suppressed to maintain a cleaner output. Subsequently, the required dataset files are read into Pandas DataFrames, enabling further processing and analysis. Pandas library is used to read and merge data from two CSV files, "studentVle.csv" and "vle.csv", presumably part of the Open University Learning Analytics dataset. These two datasets can be merged based on the 'id_site' column, which acts as a foreign key in the "vle.csv" table for further analysis. Figure 4 represents the merging process that consolidates relevant information from these datasets into a structured dataset, facilitating future analysis and model training tasks. It demonstrates the flow diagram of data processing of different data sources in the Virtual Learning Environment (VLE) and their machine learning tasks. Different VLE datasets are passing through various data processing steps.

Data preprocessing will convert the raw data into structured data for analysis and model building by cleansing and the normalization of data. After the preprocessing steps, embeddings are created, and these embeddings are further converted into tensors. Thus, this pipeline structure illustrates the workflow from preparing and transforming the virtual learning data into structured data for analysis and predictive modeling for machine learning tasks.

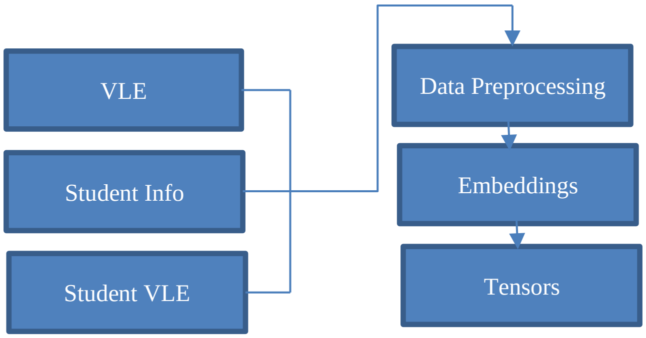


Fig. 4 Steps of data pre-processing

3.3. Feature Normalization

Feature Normalization is a vital step to make the information consistent by normalizing the values. The proposed model used MinMaxScaler to normalize the features to the range of 1 to 5 to maintain uniformity. 'sum_click' contains the aggregate of the user's interaction with resources.

Normalization of these values will make the model perform better in the training process. To normalize the feature in the range [1,5], the following formula 1 is used:

$$x^* = (x - x\_min)/(x\_max - x\_\text{min}) \qquad (1)$$

Where x is the original value.

x^* is the scaled value.
x_{min} is the minimum value.
x_{max} is the maximum value.

To make the model calculations and predictions more effective, various preprocessing steps have been implemented. Checking missing values, encoding categorical features, or adding new features are some additional preprocessing steps that are implemented to optimize the performance of the recommendation system. The common step of preprocessing is mapping different features into numbers. Mapping feature values into numbers, also known as feature encoding, is a crucial step in preparing data for machine learning models. The original OULAD database is mapped into a number of areas described in Table 2. The label encoding method is used for converting different types of features into numerical values. The embedding representation technique has been used to represent the relationships between different categories for larger and complex multi-dimensional spaces.

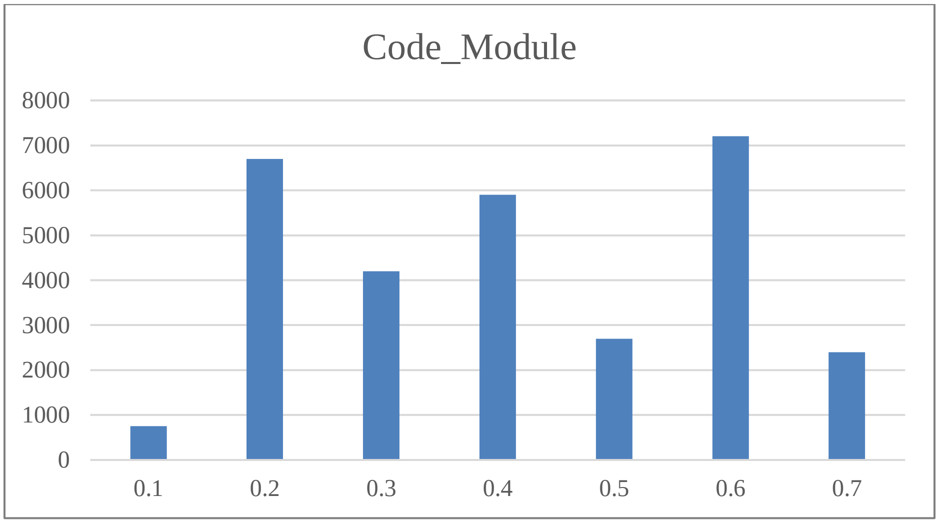
Table 2. Values of mapped features to numbers

code_module	code_presentation	age_band	highest_education	final_result	gender
AAA = 0.1	2013B = 540	0 - 35 = 0.1	A level or equivalent = 0.1	Distinction = 0.1	F = 0.1
BBB = 0.2	2013J = 720	35 – 55 = 0.2	HE qualification = 0.2	Pass = 0.2	M = 0.2
CCC = 0.3	2014B = 180	55 ≤ = 0.3	Lower than A level = 0.3	Fail = 0.3	-
DDD = 0.4	2014J = 360	-	No formal quals = 0.4	Withdrawn = 0.4	-
EEE = 0.5	-	-	Post Graduate Qualification = 0.5	-	-
FFF = 0.6	-	-	-	-	-
GGG = 0.7	-	-	-	-	-

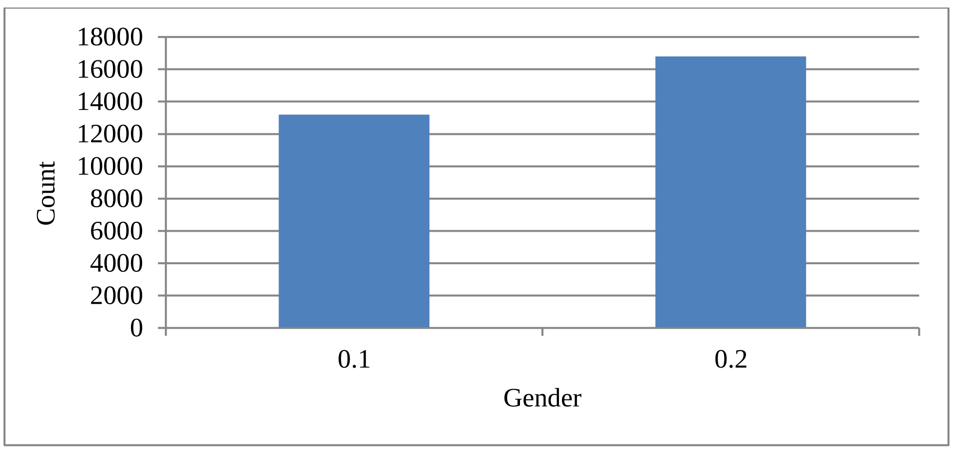
Numerical mapping on the course data, age, level of education, and scores can help to analyze the learning patterns, time spent on different resources and their distribution to see the learner engagement with resources, which supports the personalized recommendations. The distribution of features provides a better understanding of features, which makes the model more interpretable. This approach of mapping the features into numbers and then the feature distribution will guide effective personalized recommendations.

Figure 5 demonstrates the distribution of different features mapped into numbers. Figure 5(a) bar chart shows the distribution of the code_module feature. Each bar represents the distinct category of code_module. The X-axis represents the different courses in the VLE dataset, which have been mapped into numbers ranging from 0.1 to 0.7. The Y-axis represents the count, which shows how each course appears in the dataset. This distribution chart shows the course's popularity and its acceptance. It helps in understanding which course module is highly active or in demand and which needs more enrollment.

Figure 5(b) represents the bar chart distribution of the gender feature, which has been mapped into numerical values 0.1 and 0.2. X- axis represents the gender categories with values 0.1 and 0.2. The Y-axis represents the count of instances for each category. Analysis of gender distribution will help to ensure that the recommendations are not gender biased and are beneficial for both categories. Figure 5(c) displays the distribution of feature age_band. age_band features have been mapped into numerical values, which represent the different age groups in the VLE dataset. The X-axis represents the different numerical age_band values, and the Y-axis represents the frequency of each age group in the dataset. This age-group distribution is beneficial for recommending age_group appropriate resources. Figure 5 (d) Stacked bar chart displays the distribution of final_result over gender category. The final results have been mapped into numerical values. The X-axis and Y-axis represent the gender and the count of instances of final_result categories, respectively. It helps in examining the performance across the different gender categories and guiding the recommendation process.Figure 5(e) Pie chart shows the distribution of the final result category in the VLE dataset. Each segment of the pie chart represents a different category of the final result's numerically mapped value. This distribution gives deep insights into the overall performance of students. It identifies which student comes under which category (fail, pass, distinction, or withdrawn). The results help to find out which group of students needs more guidance and support to improve their outcomes.



(a)



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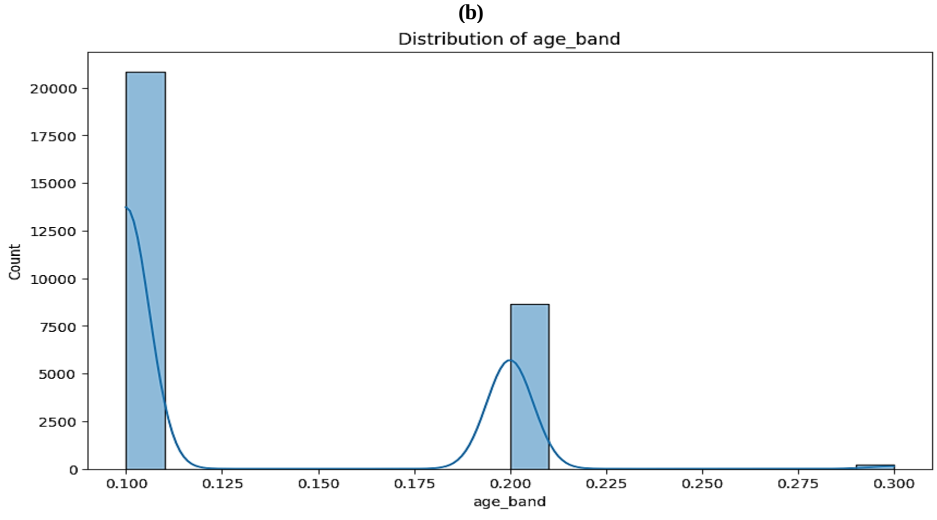

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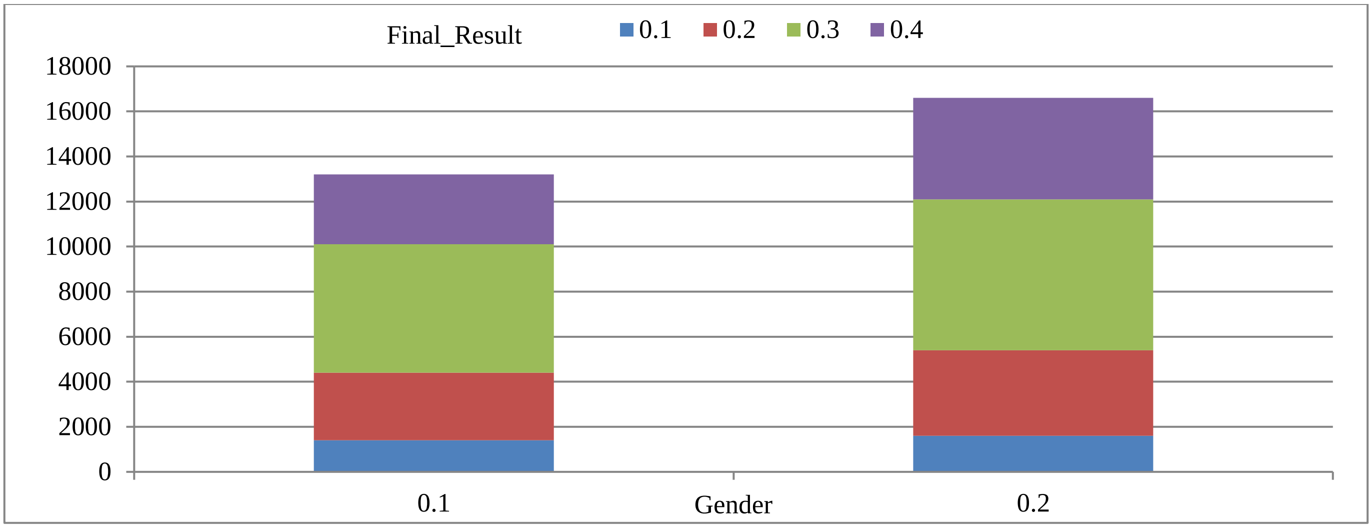
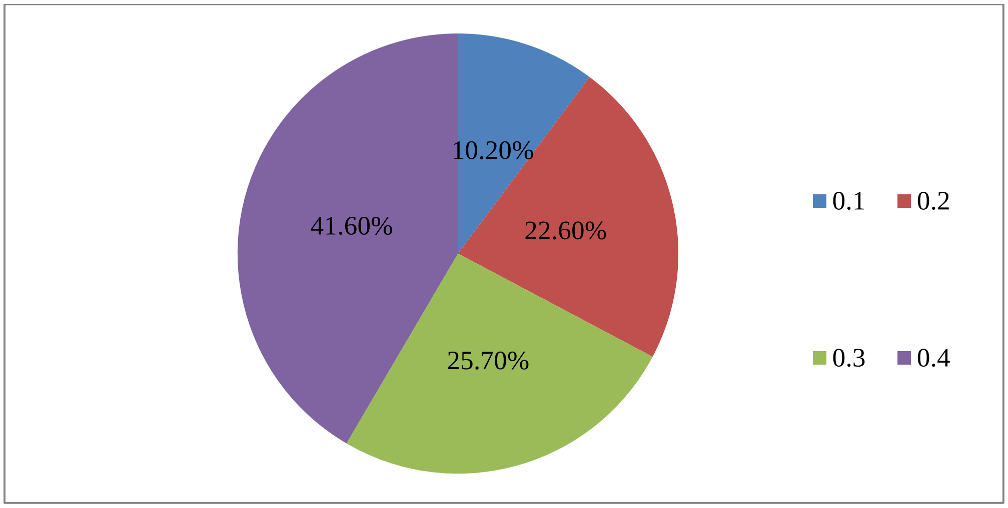


(d)



(e)

Fig. 5(a) Distribution of code_module, (b) Distribution of gender, (c) Distribution of age_band, (d) Stacked Bar chart of Gender and Final Result, and (e) Pie Chart of Final Result.

3.4. Exploratory Data Analysis (EDA)

Exploratory data analysis provides deep insights into the dataset and finds the hidden patterns of structures. It is the basic and crucial step for the development of algorithms. It gives a visual description of the dataset and makes them understand better. Starting from a collection of data from various resources, understanding the behavior of data, data patterns, its structure, visualization of data distributions with statistics, mapping the features into numbers, missing values, finding the correlation between variables to the preparation of data for modeling and then finally splits the data into training/testing datasets. An analysis of missing values is performed to ensure data integrity.

Missing values can significantly impact the acceptability and efficiency of the model's predictions. The code effectively identifies any missing data points, providing users with the necessary information to rectify and address these issues before proceeding with further analysis or model training. Using IPython.display library enables print-formatted markdown outputs within a Jupyter environment to analyze our data and check for any missing values. Data visualization, feature engineering, analyzing the correlation between the variables, preparing the data for modeling and encoding categorical variables, and splitting the training and testing datasets. This comprehensive examination of the dataset is conducted to provide detailed statistics on various aspects, such as total ratings, unique user counts, and unique products. This exploratory analysis lays a solid foundation for subsequent model-building and validation tasks, offering insights into the overall structure and distribution of the data.

3.5. Correlations Heatmap

A correlation heatmap is a graphical representation to shows how the different features are significantly related to each other. Figure 6 provides the pairwise relationship between different features of the dataset. The use of colors demonstrates the intensity of correlations. Correlation heatmap gives a better understanding and visualization of the relation of different features of the dataset in the form of a matrix. The correlation matrix shows the pairwise correlations between different features in a dataset, which signifies the correlation factor.

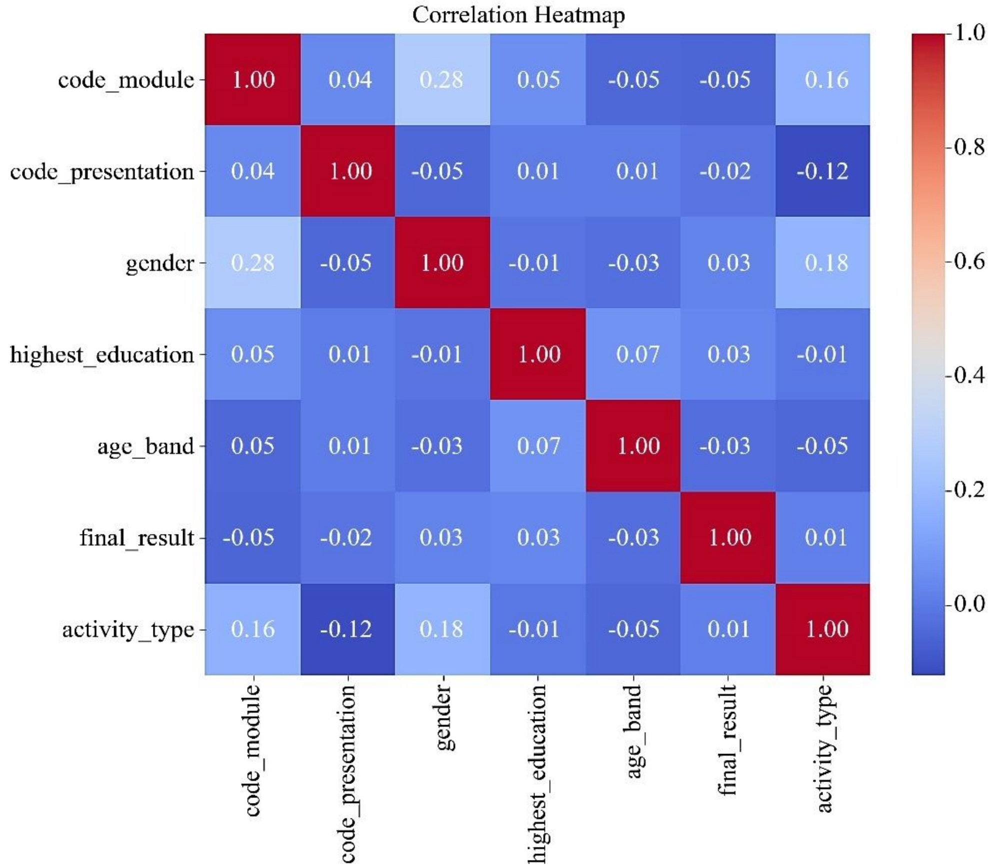


Fig. 6 Correlation test results

3.6. Enumerating Activity Types

There are different activity types available within the dataset. Understanding the diversity and prevalence of these activity types is crucial for assessing resource popularity and relevance, enabling informed decisions in the recommendation process. The obtained unique activity type in the data set. So, the activity_type are the resources students can use while enrolled in a course and represent what students should use to improve their learning experience and potentially help them to be pre-eminent in their output and learning. Activities types such as “dataplus”, “forum”, “homepage”, “content”, “resource”, “subpage”, “url”, “externalquiz”, “oucollaborate”, “ouwiki”, “quiz”, “page”, “Glossary”, “illuminate”, “dualpane”, “folder”, “questionnaire”, “htmlactivity”, “sharedsubpage”, “repeatactivity” are the resources that need to be explored by the learner to know the engagement of learner with the resources and interest in the courses which leads to the effective recommendation process. By knowing the range of activity types ensures the variety of learning resources available and how the learners are engaged with these resources. Moreover, counts of each activity type identify how frequently the resources are used and the significance of each resource in the learning process. For an effective recommendation process, it is important to identify the most relevant and impactful resources that potentially improve the learning outcomes of learners.

3.7. Resource Recommender Model

This paper introduces a collaborative filtering model tailored specifically for educational environments. The system aims to provide personalized recommendations of educational resources, leveraging the historical interactions of users within virtual learning environments. By analyzing past user behaviors, the recommendation system endeavors to optimize resource selection, ultimately enriching the learning journey for students. The recommendation system model is constructed using Collaborative Filtering and Content-based filtering. This involves the creation of a ranking model and a full recommender system model, which integrates features and labels to compute the loss and update the model parameters during training. The neural network architecture includes embedding layers for both students and resources. The embedding layers map categorical IDs to dense vectors in a lower-dimensional space. These embeddings are concatenated and passed through multiple dense layers with ReLU activation functions. The exact number of layers and units in each layer can be customized based on the complexity of the dataset and the computational resources available. Figure 7 represents the detailed proposed neural network for recommending educational resources.

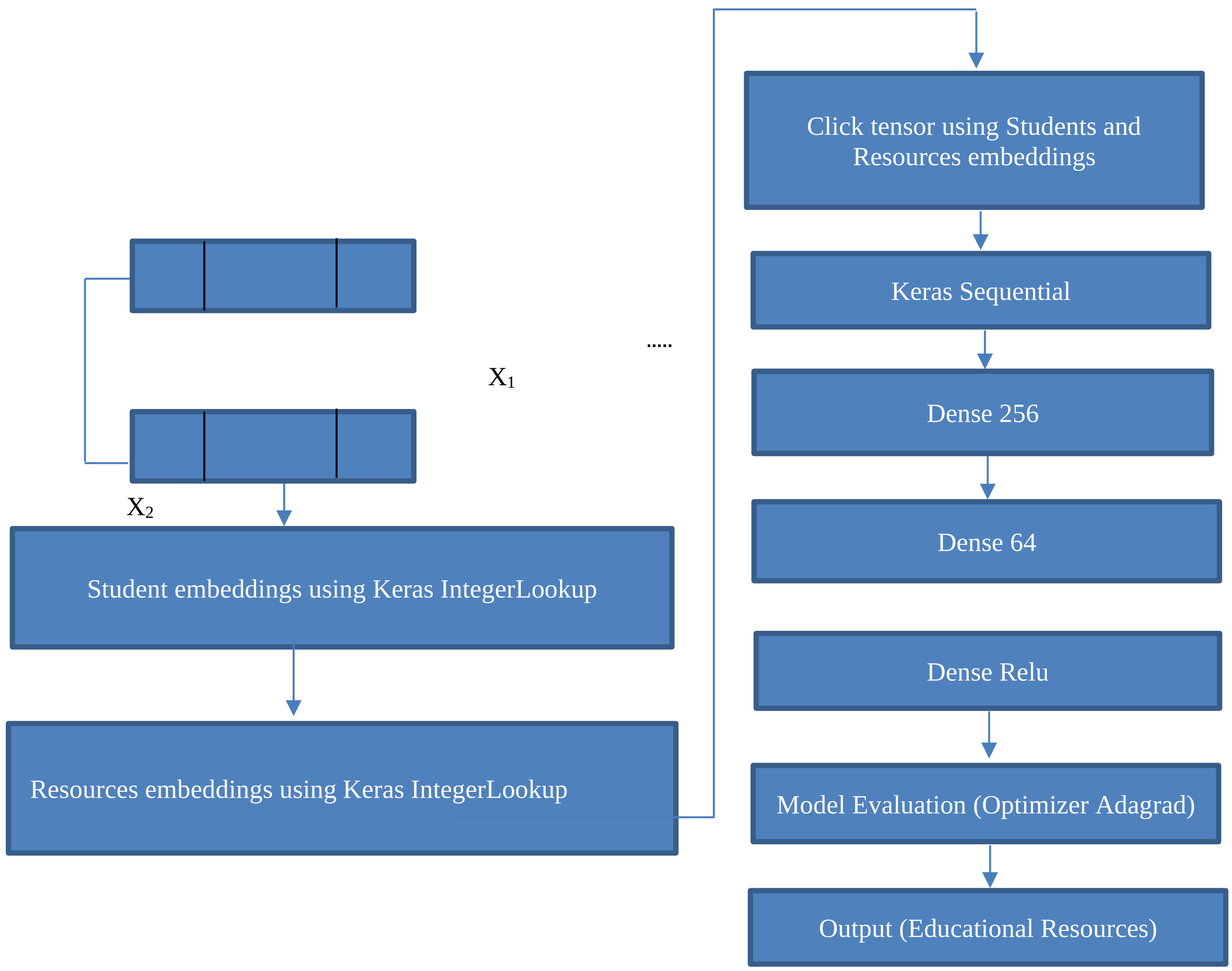


Fig. 7 Proposed network architecture

The Neural Network model is a Neural Collaborative Filtering (NCF) approach combining embeddings and dense layers for predicting resource recommendations. The components of the model are as follows:

Student-Resource Embeddings: Neural networks employ the embedding layers for both students and resources. Embedding layers map the categorial IDs to dense vectors in a lower-dimensional space.

Sequential dense layers: These embeddings are then concatenated and passed through dense layers depending on the complexity of datasets and to understand the interaction patterns.

Clicks prediction: This layer predicts the most clicked resources between users and resource interactions, which ultimately recommends resources and outputs personalized educational resource recommendations.

Adagrad Optimizer: Adagrad optimizer has been used to handle the data sparsity issue, which occurs due to fewer clicks on resources.

Resource recommender model designs to analyze the users' interactions with resources in an e-learning environment. The model utilizes collaborative filtering and content-based filtering to rank the resources that are most likely to be of users' interest. The recommendation system uses various datasets like student information, behavior, resource data, student interaction with resources, and past usage patterns to provide personalized recommendations to enhance the learners' outcomes. To learn about users' interests and styles of learning, it is required to analyze the users' historical interactions with resources.

The Resource Recommender model is designed to predict the most clicking on particular resources by the users based on their activity types and historical patterns of interaction. Embedding layers have been employed to capture student-resource interactions passed through multiple dense layers. Since the activity type represents the role associated with particular module material, and by knowing how many times the user interacts with material from the sum_click feature personalized recommendations are implicitly made by correlating the resources with courses being studied.

3.8. Components of the Model

3.8.1. Ranking Model

- Neural networks employ the embedding layers for both students and resources.
- Embedding layers map the categorial IDs to dense vectors in a lower-dimensional space.
- These embeddings are then concatenated and passed through dense layers depending on the complexity of the datasets to predict the most clicked resources.

3.8.2. Resource Recommender System Model

- This component encapsulates the ranking model and defines the evaluation task.
- It specifies the loss function and evaluation metrics, such as Mean Squared Error, Root Mean Squared Error, Binary Accuracy, Recall, and Precision.

Pseudocode: Educational Resource Recommendation System

```
Require: ds as dataset
ds: merge various datasets based on common attributes
and foreign keys

Data Pre-Processing
If  isempty(ds)
      Feature normalization
      for feature 1… 5
           ds.data=MinMaxScaler()
          scaled_data-scaler.fit_transform(ds.data)
End If

Exploratory Data Analysis
   Require: scaled_data as ds
Conduct visualization with statistical analysis.
Map features to numeric values, handle missing data, and
identify correlations.
Verify missing values.

Ranking Model
Initialize a state variable where  :
 ds.embedding_dim = 32
 Initialize student embeddings :
        self.student_embeddings = Sequential([
            IntegerLookup(),
            Embedding(input_dim, ds.embedding_dim)])
 Initialize resource embeddings :
        ds.resource_embeddings = Sequential([
            StringLookup(),
            Embedding(input_dim, ds.embedding_dim)])
Click Model:
        ds.clicks = Sequential([
            Dense(256, activation='relu'),
            Dense(64, activation='relu'),
            Dense(1)])

 Initialize the ranking model
    ranking_model_instance = RankingModel()

Require ds dataset for evaluation.
Initaite ResourceRecommenderSystemModel:
          ds.ranking_model = ranking_model_instance
          ds.task = Task(
           loss=MeanSquaredError(),
           metrics=[RootMeanSquaredError(),
BinaryAccuracy()]
        )
    compute_loss(self, features, training=False):
        student_ids = features['student_id']
        resource_ids = features['resource_id']
        click_predictions = ds.ranking_model(student_ids,
resource_ids)
        labels = features['labels']
        return ds.task.compute_loss(labels, click_predictions)

 #calculate Precision
Precision= presision_score(ds, ds.ranking_model)
 #calculate recall
Recall= recall_score(ds, ds.ranking_model)

 While ds.test_data<=5
        resource_id = entry['resource_id']
        student_rand = entry['student_rand']
        prediction =
recommender_system_instance.ranking_model(student_ra
nd, resource_id)
        test_clicks[resource_id] = prediction
End While

    # Display the top 5 recommended products
    print("Top 5 recommended products for student_rand:")
    for resource_id in sorted(test_clicks,
key=test_clicks.get, reverse=True)[:5]:
        print(resource_id)

Execute the model fitting and testing functions
Simulate(fit_model())
Simulate(test_model())
```

The schematic architecture explains each component of the proposed model and how they are integrated, aiming towards adaptive learning. The adaptive learning method improves the learning outcome by customizing the learning resources in accordance with learners' needs and abilities. Figure 8 represents the schematic architecture of the proposed recommendation model for recommending education, which combines filtering techniques with deep learning models.

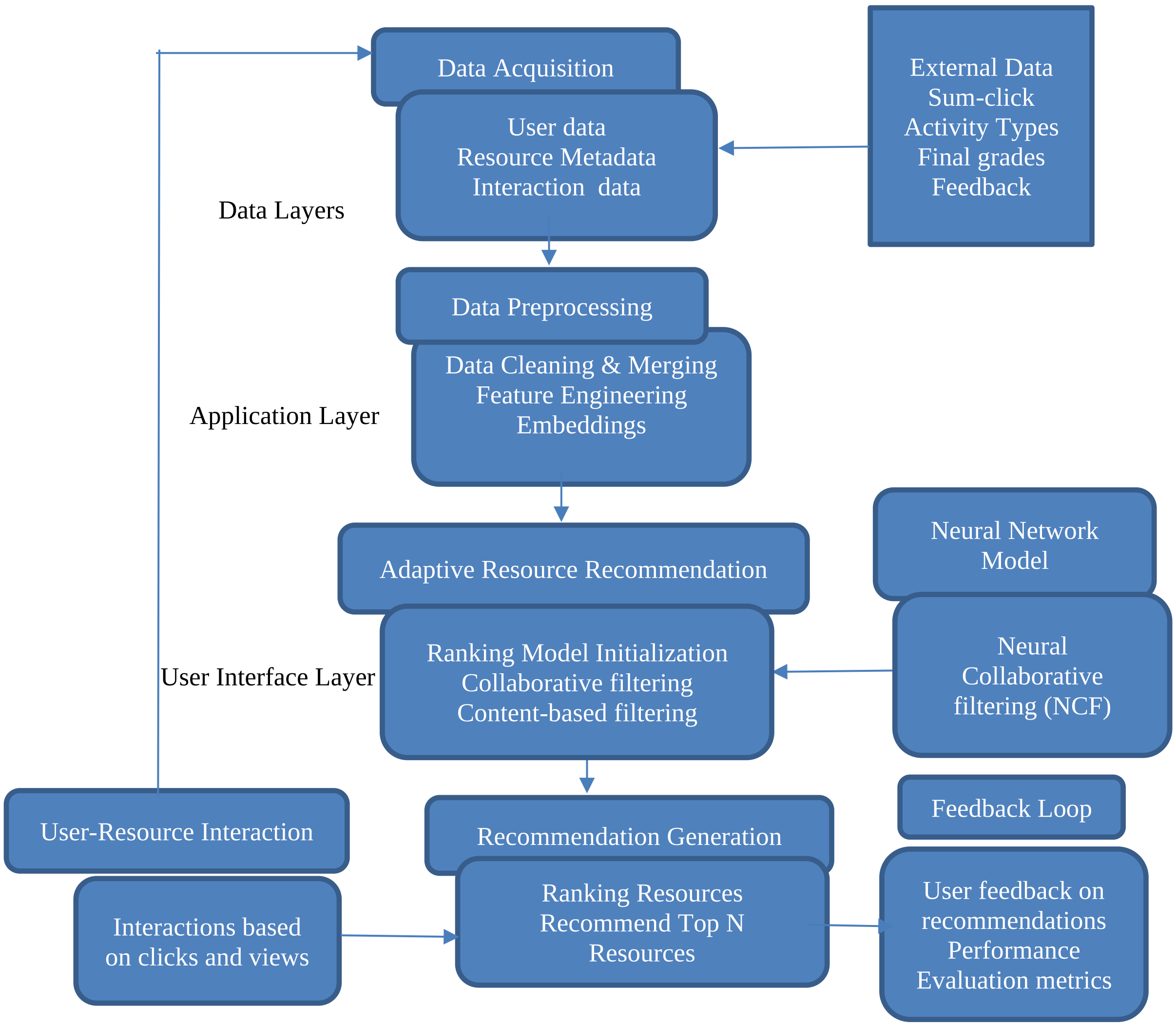


Fig. 8 Schematic architecture of a recommendation system

The above schematic diagram of the recommendation system consists of three layers data layer, the application layer, and the user-interface layer. The data acquisition layer collects the essential data for the designing of the recommender system. The OULAD dataset has been acquired for this work. User data contains student demographics, history of how they interact with data, and course registrations. Resource metadata contains the details about learning resources, the type of content it contains, and the role associated with the resource and interaction data consists of attributes like sum_click for tracking users' actions with VLE data, and some external data has been loaded for further pre-processing steps. The Data Pre-processing and Feature Engineering phase cleans and normalizes the data to make it an input for the recommendation model. It ensures data consistency and uniformity.

The application layer consists of advanced hybrid techniques of filtering, composed of collaborative filtering and content-based filtering approaches. A ranking model with Neural collaborative filtering is used to predict the likelihood of the user's interest in resources. Embedding layers capture the user-resource interactions and finally output the ranking score based on the students' engaging with particular resources. The higher the score, the more relevance of resources. The recommendation generation layer enables personalized recommendations by generating the top N relevant resources for users, by assigning scores to resources for each user and ranking them based on predicting the likelihood of users' interest. This layer satisfies the user's needs by ensuring the users get the most relevant resource. The user interface layer captures the user-resource interactions on recommended resources. It tracks the clicks and views for recommendation continual improvements. The user feedback loop will evaluate the recommendation performance and update the system accordingly. It ensures that the system will adapt to the dynamic user preferences and act accordingly.

3.9. Xai Explanation of the Proposed Model

The proposed resource recommender model is designed with an emphasis on improving the learning outcomes of learners and enhancing the learning experience. It is done by analyzing which resources are more likely to be of users' interest. XAI gives a detailed explanation of how the designed model makes more appropriate recommendations by knowing the users' interaction with resources and past interactions. XAI provides the following key points:

- The objective of the model- For effective personalized learning and to improve the learning outcomes of the learners, the model aims to predict the activity type associated with the learning resources (discussion forums, video-conferencing, Audio-only conferencing, educational web page interaction, dual pane) which users are most likely to engage while doing their courses. Predictions are based on users' past interactions and current activity types.
- Techniques used- The hybrid technique, composed of Collaborative filtering and content-based filtering techniques, has been utilized for the ranking of the resources and the recommendation of the resources. Embedding layers have been employed to capture the user resources' complex interactions, passing through multiple dense layers to predict the most clicked resources.

- Detailed data inputs- Learners' demographic information along with their enrollments in particular courses, user preferences, user interaction logs(clicks), time spent on particular resources, and metadata about the learning resources such as the type of content and the role associated with each course(activity type), Interaction data includes how the users interacted with resources earlier and frequency of interactions, usage pattern by aggregating the data on the number of clicks with resources over time.

- Embedding and dense layers- Embedding layers are employed to capture the complex relationship between users and resources. These layers map the latent representations of both students and resources and learn user-resource interaction patterns. It is difficult to find it differently from the raw input. Consider a case when students have similar learning behavior and give similar embeddings but may have explicitly different preferences. Then these embeddings are concatenated and passed through dense layers to identify the complex relationships between different features (interaction history with resources, activity type) to make predictions.
- Model predictions- This model considers the activity type, such as (audio, video, or quiz), in which the user is currently interacting or previously engaged in the past. This aids in predicting which type of resource the user is most likely to click next. To recommend the resources based on users' historical interaction patterns, a sum-click on different types of resources is used, which predicts the users' interest in a particular resource material.

- Personalized recommendations- When the types of resources within particular courses are correlated with the frequency of interactions, personalized recommendations can be made to align with users' learning patterns and enhance the outcomes of learners.

3.10. Model Training and Evaluation

The proposed model divides the OULAD dataset into 1 training set and 1 testing set with an 80 to 20% ratio, for the quality measures of recommendations, recall, precision and accuracy evaluation metrics are calculated. Finally, the recommender model recommends the top N resources to the learners. To reduce the risk of errors and to improve the models' accuracy, the proposed model is compiled. Adagrad optimizer is chosen with a learning rate of 0.1. Shuffling and batching are integral parts of the preprocessing of the training dataset. Shuffling provides a unique order of the training dataset in each epoch to improve the model's learning. It demotes biased training and prevents the model from learning the same patterns of the dataset. To improve the computational efficiency of the model batching technique divides the training data set into smaller batches and feeds them to the model to process multiple data samples simultaneously. The caching process improves the performance of the model by providing the frequently accessed dataset during the training process. It is the high-speed storage of data that handles the data requests briskly.

3.11. User Recommendation Scenario with XAI

This implied scenario exemplifies how the trained model selects a random user from the test dataset and generates the top N recommendations for the user. This process stimulates the personalized recommendation affair in users to achieve their specific goals and tasks, which ultimately enhances the users' performance and outcomes. The model was subjected to 10 epochs. Each epoch consists of 22 iterative steps during the training process. This iteration process influences the driving process experience to evolve the outcome. Use case scenarios for a clear explanation of how the whole process takes place so that the model becomes more trustworthy and interpretable both for students and educators.

Consider the case of a learner who engages with video lectures more frequently. The model interprets the activity type of learner by analyzing the number of clicks on virtual resources. The Recommender Model learns this user and resource interaction pattern. For a new login session, the new video tutorials are recommended to the learner related to the current course content. The recommendations are based on the resource similarities with those users who have interacted before and the past behavior and preferences of the users. By doing this, recommendations will enhance the engagement and learning outcomes of learners.

3.12. XAI Output Interpretation

The performance of the model can be interpreted to focus on a positive impact on learning resource utilization and user engagement with resources. To optimize the performance of the recommender system, it is important to understand the relevancy of recommendations of resources with users' preferences. Eventually, the model analyzes the sum_click based on the log data of interactions with resources and recommends the top N resources to students from the dataset. This section illustrates how the designed educational recommender system provides personalized recommendations coordinated with users' needs and preferences. XAI with resource recommender model provides a detailed overview of the model, various data inputs, and components of the model, explaining predictions of the model, and the reason behind the predictions to make the model more user-trustworthy and interpretable. The model results in a ranking list of resources based on the prediction of users' clicking on these resources.

This ranking has been determined by the activity type, users' historical patterns, and the embedding representations. For example, for learners preparing for the finals, the learners' learning pattern shows the preferences for the "externalize" resource type, and then the model will prioritize recommending "externalquiz" as the top recommendation over other resources. The models' predictions are highly explainable and exhibit transparency about why certain resources are recommended. Some resources are prioritized over other resources in the recommendation process because the embeddings for that resource are highly correlated with users' historical resource interaction and present activity type. By understanding the contribution of different attributes, the models can be more interpretable.

3.13. Performance Evaluation Metrics

The quality of the recommendations by the model can be evaluated using various evaluation metrics. The performance of the model can be assessed by the test dataset. To find the discrepancy between the actual values and the predicted values, metrics like Root Mean Squared Error and Binary Accuracy are calculated. Adaptability is are scalability factor that highlights the insurance of the model that performs better in a dynamic environment with new users and resources. RMSE, binary accuracy, recall, precision, loss, regularization loss, and total loss are calculated.

RMSE: It measures the difference between the actual values and the predicted values by the model. A decrease in the RMSE value indicates less discrepancy between values over epochs.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y\hat{}_i)^2} \quad (2)$$

Where n is the total number of observations

y_i are the actual values
$y\hat{}_i$ are the observed values

Accuracy: Accuracy is the ratio of true predictions to the total number of predictions to measure the quality of the model. The consistently high binary accuracy suggests that the model is performing well in classifying inputs.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Where TP= True Positive, TN= True Negative, FP= False Positive, FN= False Negative

Loss: The loss metric represents how well the model is making predictions relative to the true labels. The decreasing loss values indicate that the model's predictions are improving over epochs.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y\hat{}_i)\ 2 \quad (4)$$

Where y_i is the actual value, and y^i is the predicted value

Regularization Loss: Regularization is used to prevent overfitting by penalizing complex models. A zero-regularization loss suggests that either no regularization was applied or its contribution to the total loss is negligible. It improves the model's generalization ability.

Total Loss: This combines the loss from model predictions with any regularization loss. Consistency between the loss and regularization loss indicates stable model performance.

Total Loss = Loss function + Regularization Loss (5)

Recall: It is defined as the ratio of true positive predictions (TP) to the sum of true positive predictions and false negative (FN) predictions. It is used to measure the effectiveness of a model in identifying all relevant instances in the dataset.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

Where TP = number of correctly predicted positive instances.

FN = number of positive instances that are incorrectly predicted as negative.

Precision: Precision is defined as the ratio of true positive predictions (TP) to the sum of true positive predictions and false positive (FP) predictions.

$$\text{Precision}=\frac{TP}{TP+FP} \quad (7)$$

Where TP= Number of correctly predicted positive instances.

FP= Number of negative instances which are incorrectly predicted as positive

4. Results and Discussion

The recommendation system successfully generated a list of “Top 5 recommended products for User 41489”, which includes items such as “dataplus”, “oucollaborate”, “page”, “url” and “resource”.

These recommendations demonstrate the model’s ability to leverage the user’s characteristics or past behavior to offer personalized suggestions tailored to their preferences and needs. The fact that the recommended items align with the user’s interests or learning patterns suggests that the model has effectively learned from the dataset and can provide relevant recommendations to enhance the user’s learning experience. Recommendations are based on user preferences and behavior within the virtual learning environment, and they implicitly reflect the course recommendations. By knowing the users’ learning styles and interests, personalized recommendations are tailored to suit individual preferences. Frequent engagement with parameters like “Quiz” and “Assignment submission” is correlated with the courses being studied to make implicit course recommendations. User feedback on recommended resources helps refine future recommendations, ensuring relevance and effectiveness. Upon evaluation, presumably on a validation or test set, the model outputs the following metrics:

Root Mean Squared Error (RMSE) :0.06046643108129501, suggesting a slight improvement from the final training

Accuracy:Remains high at 99.73287582397461%. Recall:1.0000

Precision:1.0000.

Loss:0.005082578863948584.

Regularization Loss:0

Both these metrics are consistent with the final training epoch, indicating the model’s performance is stable when presented with new data.

The comparative analysis table of recommendation models highlights the effectiveness of the proposed model across the performance evaluation metrics. The evaluated results of the proposed model are compared with the other methods of related work. Table 3 and Figure 9 demonstrate the best performance of the proposed model among all models.

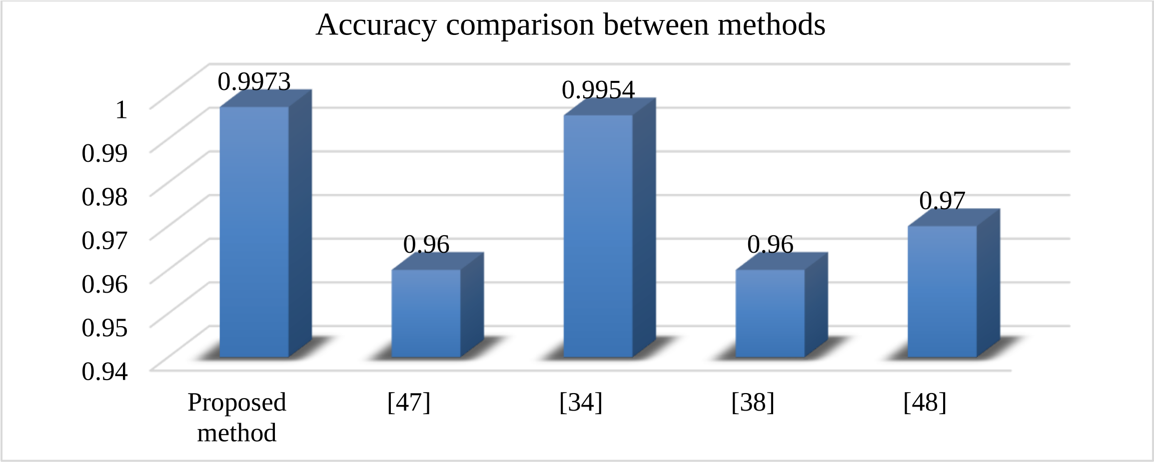
All the evaluations are performed on the OULAD dataset. Our model provides more desirable results at different evaluation metrics. The proposed ALRS model personalizes the learning paths relevant to individual users’ demographics and preferences. This system integrates K -clustering, content-based filtering, and a random forest classifier to predict the learner’s preferences and generate personalized course suggestions [49]. An integrated model was developed to classify learners based on their learning activity clicks.

This model employs a combination of machine learning algorithms, SVM, KNN, RF, and LR. Mapping the activity clicks and learning styles, the assessment methods are employed for predicting the performance of learners. Our proposed method achieves accuracy that is significantly higher than this method [47]. The ShuffleNet V2 technique is evaluated to predict the number of students who have recommended and not recommended the learning site of interest. The proposed model offers the highest experimental results when compared to the model [34]. By leveraging the capabilities of MLP, BiLSTM, and LSTM networks enhanced with an attention method, the system offers highly accurate and personalized resource recommendations. This study achieves an accuracy of 0.96, which is also lower than that of our proposed model [38]. The AISAR system represents a significant advancement in e-learning by integrating artificial intelligence to provide a comprehensive and personalized learning experience. By accurately assessing student performance, clustering them into meaningful groups, predicting future performance, and offering tailored recommendations, the system enhances the educational process. An increase in accuracy demonstrates the better performance of the proposed model [48]. Figure 9 demonstrates that the proposed model outperforms all the evaluated parameters of the other implemented methods.

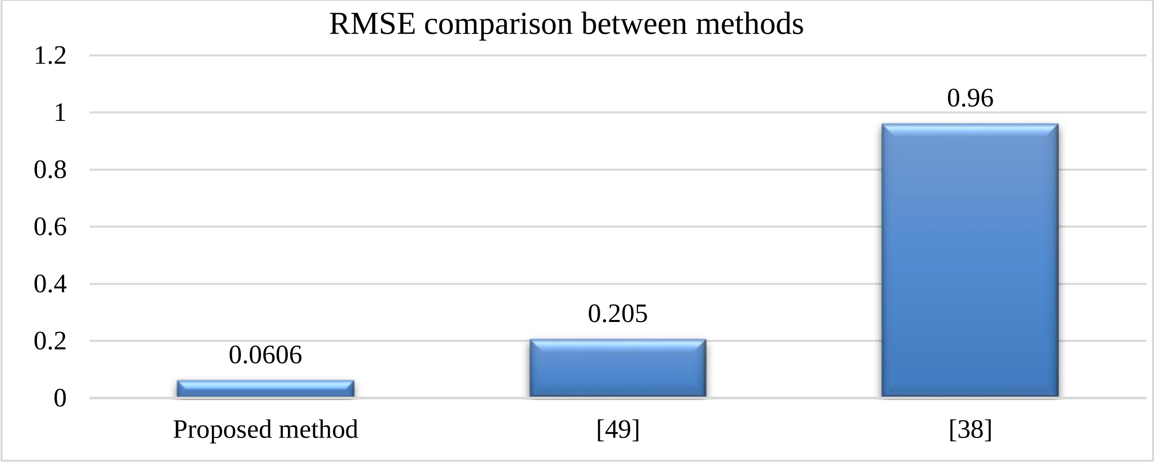
Table 3. Comparative performance analysis

Models	Accuracy	RMSE	Loss	Total Loss	Recall	Precision	F1-score	Reference
Training 1st epoch	0.9047	0.259	0.063	0.0632	0.953	1	-	Proposed Model
Final Evaluation	0.9973	0.061	0.005	0.005	1	1	-	
ALRS	-	0.205	-	-	0.89	0.92	-	[49]
SVM	0.96	-	-	-	0.96	0.97	0.97	[47]
KNN	0.98	-	-	-	0.98	0.99	0.98	
RF	0.96	-	-	-	0.96	0.97	0.97	
Logistic Regression	0.95	-	-	-	0.97	0.96	0.97	

ShuffleNet V2 with MBOA	0.9954	-	-	-	0.98	0.98	0.99	[34]
Train (LSTM, BiLSTM, MLP)	0.959	0.08	-	-	-	-	-	[38]
Test (LSTM, BiLSTM, MLP)	0.96	0.96	-	-	0.96	0.96	-	
AISAR system	0.9721	-	-	-	0.97	0.91		[48]



(a)



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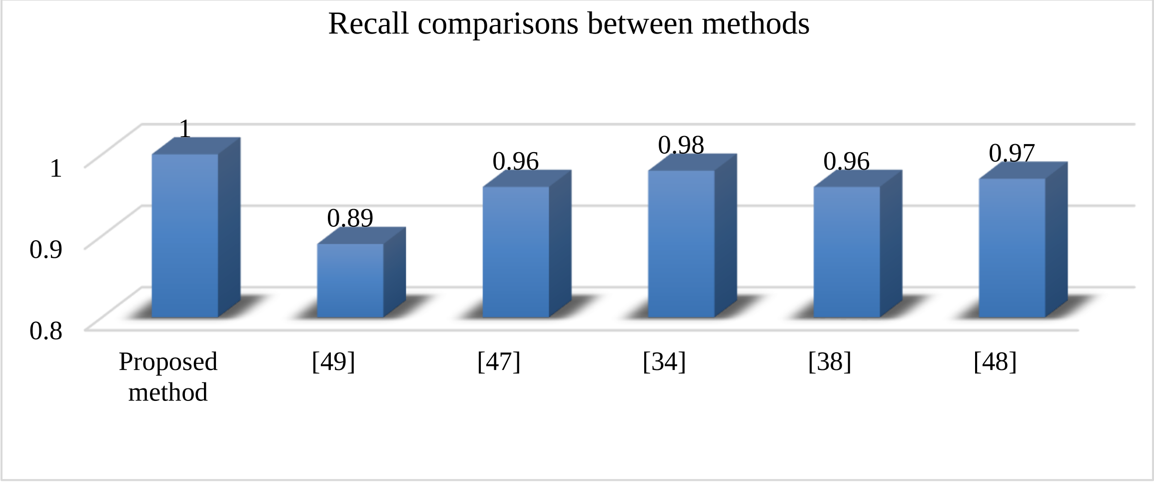

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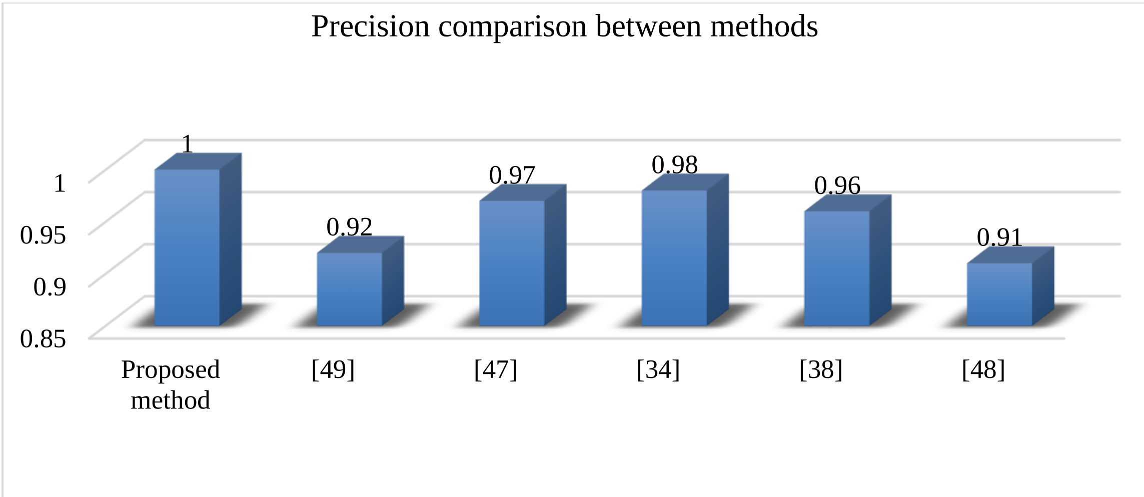

(d)

Fig. 9(a) Accuracy results Comparison, (b) RMSE results Comparison, (c) Recall results Comparison, and (d) Precision results Comparison.

Overall, the training and evaluation metrics indicate that the model has performed well. The high binary accuracy, low RMSE, and consistent loss metrics throughout training and evaluation suggest that the model is making accurate predictions with minimal errors. The model's proficiency in keeping accurate evaluation metrics with minimal errors results across different phases of training and evaluation underscores its reliability and effectiveness in providing accurate recommendations. Evaluation metrics result shows the adaptability and scalability factors demonstrate the recommendation models' potential in a dynamic environment.

4.1. Significance of Educational Recommender System for Enhancing Learning Outcomes

The output of an Educational recommender system signifies the enhancement of learning outcomes with observable improvements in the learners' performance. The ML models, such as multilabel, provide a comprehensive recommendation, including pedagogical, assessment, and content-related programmes, tailored to each learning content. The implementation at Jouf University showed that when the recommended actions were applied, student learning experiences improved, evidenced by: Higher Course Outcome (CO) attainment levels in subsequent course offerings. Positive feedback from students and faculty. Reduction in the number of courses marked as "low performance" in outcomes. These empirical improvements provide direct evidence that the system's recommendations correlate with better student learning results [50].

Since the learning style and knowledge level of each learner are different, thus, to cope with the diverse needs of learners, the recommendation system should generate recommendations tailored to their diverse needs. Content-based filtering approach generates the recommendation list by pre-processing the data and predicting the learners' performances. The proposed system contributes to better learning outcomes by personalizing learning pathways, adaptive content recommendations, and continuous feedback through E - Assessment. The three-tiered e-assessment module provides a diagnostic assessment to identify baseline knowledge. Formative assessment to monitor progress. Revision module to reinforce weak areas. This feedback loop ensures ongoing learning improvement and self-awareness [51].

The system has utilized ALBERT's optimized architecture to generate personalized learning recommendations based on students' demographics, the behaviour of learners, and interactions. The proposed optimized architecture generates the recommendations that enhance the learning outcomes of learners, improve the recommendation accuracy, boost the academic performance, increase learner engagement and meet the learners' satisfaction. Personalized learning recommendations using the ALBERT-powered system result quantifiable positive impact on the grades of learners.

High-quality personalized recommendations effectively work by retaining the knowledge, improving the learning rate, and increasing user engagement. Engagement metrics (time spent on tasks, interaction frequency, etc.) saw significant improvement. Surveys revealed that learners found the recommendations understandable, well-timed and relevant [52].

The objective of this study is to suggest the relevant online learning resources to students with weak CLOs (Course Learning Outcomes). Before the Outcome Based Education (OBE) model, the students were completely relied on either the course teacher's suggestions or finding the relevant resources by themselves. To achieve this objective, firstly Student-CLO matrix is formed, and by using Bi-clustering, groups of students having similar performances in different CLOs are identified. This method has been previously used in bioinformatics for gene expression analysis.

The resultant bi-clusters are then uniformly sorted to work out a reinforcement learning environment. Students' initial state is determined by cosine similarity. The online educational tutorials, YouTube videos, E-learning books, and research articles are then suggested to improve their course learning outcomes using a mobile application. This system provides a scalable and adaptive method for improving student performance by addressing individualized learning needs. Performance improvements can be quantitatively measured through before-and-after CLO attainment scores, which provide clear evidence of learning outcome enhancement [53].

This research work enhances the learning outcomes by providing personalized, data-driven recommendations that align with each user's engagement patterns, preferences. It contributes to improved learning outcomes by personalized the learning paths by using sum_click values, user interactions and external data to tailor recommendations. The user feedback module helps to evolve recommendations over time, helping the learners to get the right resources at the correct time. The neural collaborative filtering NCF model predicts the accurate interaction probability based on embeddings of users and resources. The resources with high interaction probability value indicate the more relevant resources, which increase the user's engagement. Since the

sum_click data and activity types are monitored, which enables the identification of students at risk needs the timely intervention by system. The recommender system provides the list of top N relevant resources, which reduces the overloading of material. It is time effective for learners by just focusing on the quality material that aligns to their needs and interests rather than spending time on irrelevant materials.

5. Conclusion and Future Scope

The proposed research addresses the critical challenges in E-learning environments, such as personalized learning, user engagement, and resource relevance, focusing on developing a resource recommendation system to enhance the learning outcomes. Integration of advanced techniques like collaborative filtering, content-based filtering, and Neural collaborative filtering creates a hybrid resource recommendation system that improves the accessibility and quality of E-learning. The proposed model achieved an average accuracy of 0.9973 and a Root Mean Squared Error (RMSE) of 0.0606. Ranking model uses the sum_click metric to determine the user preferences and relevance of the resources and recommends the top N relevant resources to the users.

The proposed recommendation system can be integrated with different learning environments in various learning contexts. Its adaptive nature and scalability make it suitable for different learning environments. It is highly flexible and can easily be customized to meet the users' preferences and needs. Its flexibility allows for customization to meet specific educational requirements and user preferences. The multi-dimensional approach of incorporating features such as learners' demographics, interaction metadata, external data, learners' engagement with content, and resource data ensures data-driven recommendations.

XAI principles ensure that the model exhibits both transparency and interpretability, factors that explain why certain recommendations are made. To get deep insights into why certain resources are recommended, the model builds trust with users. Rule-based recommendations can provide transparency rules to explain the reason behind each recommendation, making the process smooth and understandable.

Additionally, model-agnostic techniques such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) can provide post-hoc explanations by highlighting the features that contribute most to each recommendation. Future work may emphasize the integration of more advanced features incorporating real-time feedback mechanisms, and additional data sources exploration to further refine and enhance the system's capabilities. The outcomes of this research can further impact the investigations in the field of recommender systems for educational data, thereby opening new prospects of research and extending its scope further in the developing world of intelligent systems.

Author Contributions

All authors have contributed to this paper.

Data Availability

The dataset used in the work is openly accessible at https://archive.ics.uci.edu/dataset/349/open+university+learning+analytics+dataset.

References

[1] Julián Monsalve-Pulido et al., "Autonomous Recommender System Architecture for Virtual Learning Environments," *Applied Computing and Informatics*, vol. 20, no. 1/2, pp. 69-88, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Wangmei Chen et al., "Applying Machine Learning Algorithm to Optimize Personalized Education Recommendation System," *Journal of Theory and Practice of Engineering Science*, vol. 4, no. 1, pp. 101-108, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Kerstin Wagner et al., "Personalized and Explainable Course Recommendations for Students at Risk of Dropping Out," *Proceedings of the 15th International Conference on Educational Data Mining*, 2022. [Google Scholar] [Publisher Link]

[4] Samina Amin et al., "An Adaptable and Personalized Framework for Top-N Course Recommendations in Online Learning," *Scientific Reports*, vol. 14, no. 1, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Hadis Ahmadian Yazdi, Seyyed Javad Seyyed Mahdavi, and Hooman Ahmadian Yazdi, "Dynamic Educational Recommender System Based on Improved LSTM Neural Network," *Scientific Reports*, vol. 14, no. 1, pp. 1-119, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Shadi Atalla et al., "An Intelligent Recommendation System for Automating Academic Advising Based on Curriculum Analysis and Performance Modeling," *Mathematics*, vol. 11, no. 5, pp. 1-25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jinnie Shin, and Okan Bulut, "Building an Intelligent Recommendation System for Personalized Test Scheduling in Computerized Assessments: A Reinforcement Learning Approach," *Behavior Research Methods*, vol. 54, no. 1, pp. 216-232, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Samina Amin et al., "Developing a Personalized e-Learning and MOOC Recommender System in IoT-Enabled Smart Education," *IEEE Access*, vol. 11, pp. 136437-136455, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Shuai Zhang et al., "Deep Learning Based Recommender System: A Survey and New Perspectives," *ACM Computing Surveys*, vol. 52, no. 1, pp. 1-38, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] John K. Tarus, Zhendong Niu, and Abdallah Yousif, "A Hybrid Knowledge-Based Recommender System for E-Learning Based on Ontology and Sequential Pattern Mining," *Future Generation Computer Systems*, vol. 72, pp. 37-48, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Paul Covington, Jay Adams, and Emre Sargin, "Deep Neural Networks for YouTube Recommendations," *Proceedings of the 10th ACM Conference on Recommender Systems*, Boston Massachusetts, USA, pp. 191-198, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[12] Vusumuzi Maphosa, and Mfowabo Maphosa, "Fifteen Years of Recommender Systems Research in Higher Education: Current Trends and Future Direction," *Applied Artificial Intelligence*, vol. 37, no. 1, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Boxuan Ma et al., "CourseQ: The Impact of Visual and Interactive Course Recommendation in University Environments," *Research and Practice Technology Enhanced Learning*, vol. 16, no. 1, pp. 1-24, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Hsiao-Chien Tseng et al., "Building an Online Adaptive Learning and Recommendation Platform," *Emerging Technologies for Education: First International Symposium*, Rome, Italy, pp. 428-432, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[15] Stanislav Kuznetsov et al., "Reducing Cold Start Problems in Educational Recommender Systems," *2016 International Joint Conference on Neural Networks*, Vancouver, BC, Canada, pp. 3143-3149, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[16] Sajid Ali et al., "Explainable Artificial Intelligence (XAI): What We Know and What is Left to Attain Trustworthy Artificial Intelligence," *Information Fusion*, vol. 99, PP. 1-52, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Andrew Saxe, Stephanie Nelli, and Christopher Summerfield, "If Deep Learning is the Answer, What is the Question?," *Nature Reviews Neuroscience*, vol. 22, no. 1, pp. 55-67, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Zewen Li et al., "A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 12, pp. 6999-7019, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Giulia Vilone, and Luca Longo, "Notions of Explainability and Evaluation Approaches for Explainable Artificial Intelligence," *Information Fusion*, vol. 76, pp. 89-106, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Finale Doshi-Velez, and Been Kim, "Towards a Rigorous Science of Interpretable Machine Learning," *Arxiv*, pp. 1-13, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[21] Alonso José Maria, "Explainable Fuzzy Systems-Paving the Way from Interpretable Fuzzy Systems to Explainable AI Systems," *Studies in Computational Intelligence*, vol. 970, pp. 1-253, 2021. [Google Scholar] [Publisher Link]

[22] Judea Pearl, and Dana Mackenzie, *The Book of Why: The New Science of Cause and Effect*, Penguin Books Limited, pp. 1-432, 2018. [Google Scholar] [Publisher Link]

[23] Hassan Khosravi et al., "Explainable Artificial Intelligence in Education," *Computer and Education: Artificial Intelligence*, vol. 3, pp. 1-22, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Tim Miller, "Explanation in Artificial Intelligence: Insights from the Social Sciences," *Artificial Intelligence*, vol. 267, pp. 1-38, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ernest L. Boyer, *Scholarship Reconsidered: Priorities of the Professoriate*, Carnegie Foundation for the Advancement of Teaching, pp. 1-147, 1990. [Google Scholar] [Publisher Link]

[26] Carolin Kreber, "Reflection on Teaching and the Scholarship of Teaching: Focus on Science Instructors," *Higher Education*, vol. 50, pp. 323-359, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[27] Margaret Price et al., "Feedback: All That Effort, But What is the Effect?," *Assessment and Evaluation in Higher Education*, vol. 35, no. 3, pp. 277-289, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[28] Ashima Kukkar et al., "A Novel Methodology using RNN+ LSTM+ ML for Predicting Students' Academic Performance," *Education and Information Technology*, vol. 29, pp. 14365-14401, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Veena Grover et al., "Proposed Hybrid Model in Online Education," *EAI Endorsed Transactions on Internet of Things*, vol. 10, pp. 1-7, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[30] Qionghao Huang, and Yan Zeng, "Improving Academic Performance Predictions with Dual Graph Neural Networks," *Complex and Intelligent Systems*, vol. 10, pp. 3557-3575, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Hao Luo et al., "Object-Oriented Online Course Recommendation Systems Based on Deep Neural Networks," *Journal of Theoretical and Applied Information Technology*, vol. 102, no. 3, pp. 1276-1287, 2024. [Google Scholar] [Publisher Link]

[32] Yan Zhu, "Personalized Recommendation of Educational Resource Information Based on Adaptive Genetic Algorithm," *International Journal of Reliability, Quality and Safety Engineering*, vol. 30, no. 2, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] Hadi Ezaldeen et al., "Semantics Aware Intelligent Framework for Content-Based E-Learning Recommendation," *Natural Language Processing Journal*, vol. 3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[34] Dudla Anil Kumar, and M. Ezhilarasan, "Shufflenetv2: An Effective Technique for Recommendation System in e-Learning by User Preferences," *Multi-disciplinary Trends in Artificial Intelligence: 16th International Conference*, Hyderabad, India, pp. 179-191, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[35] Dina Fitria Murad et al., "Personalization of Study Material based on Predicted Final Grades using Multi-Criteria User-Collaborative Filtering Recommender System," *Education and Information Technologies*, vol. 25, no. 6, pp. 5655-5668, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[36] Jing Li, and Zhou Ye, "Course Recommendations in Online Education based on Collaborative Filtering Recommendation Algorithm," *Complexity*, vol. 2020, no. 1, pp. 1-10, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[37] Gongwen Xu et al., "Personalized Course Recommendation System Fusing with Knowledge Graph and Collaborative Filtering," *Computational Intelligence Neuroscience*, vol. 2021, no. 1, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[38] Hadis Ahmadian Yazdi, Seyyed Javad Seyyed Mahdavi Chabok, and Maryam Kheirabadi, "Dynamic Educational Recommender System Based on Improved Recurrent Neural Networks Using Attention Technique," *Applied Artificial Intelligence*, vol. 36, no. 1, pp. 1-24, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[39] Jamal Mawane, Abdelwahab Naji, and Mohamed Ramdani, "Unsupervised Deep Collaborative Filtering Recommender System for e-Learning Platforms," *Smart Applications and Data Analysis: Third International Conference*, Marrakesh, Morocco, pp. 146-161, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[40] Ming Gao, Yonghan Luo, and Xiaonan Hu, "Online Course Recommendation using Deep Convolutional Neural Network with Negative Sequence Mining," *Wireless Communications and Mobile Com*puting, vol. 2022, no. 1, pp. 1-7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[41] Xu Zhu, and Zhaofa Zhang, "Precise Recommendation Algorithm for Online Sports Video Teaching Resources," *EAI Endorsed Transactions on Scalable Information Systems*, vol. 10, no. 2, pp. 1-9, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[42] Jun Xiao et al., "A Personalized Recommendation System with Combinational Algorithm for Online Learning," *Journal of Ambient Intelligence and Humanized Computing*, vol. 9, no. 3, pp. 667-677, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[43] Kumar Abhinav et al., "LeCoRe: A Framework for Modeling Learner's Preference," *11th International Conference on Educational Data Mining*, Buffalo, New York, US, 2018. [Google Scholar] [Publisher Link]

[44] Soulef Benhamdi, Abdesselam Babouri, and Raja Chiky, "Personalized Recommender System for e-Learning Environment," *Education and Information Technologies*, vol. 22, pp. 1455-1477, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[45] Sunita B Aher, and L.M.R.J. Lobo, "A Framework for Recommendation of Courses in e-Learning System," *International Journal of Computer Applications*, vol. 35, no. 4, pp. 21-28, 2011. [Google Scholar] [Publisher Link]

[46] Jakub Kuzilek, Martin Hlosta, and Zdenek Zdrahal, "Open University Learning Analytics Dataset," *Scientific Data*, vol. 4, no. 1, pp. 1-8, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[47] Ahmed Rashad Sayed et al., "Predict Student Learning Styles and Suitable Assessment Methods Using Clickstream," *Egyptian Informatics Journal*, vol. 26, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[48] Wala Bagunaid, Naveen Chilamkurti, and Prakash Veeraraghavan, "Aisar: Artificial Intelligence-Based Student Assessment and Recommendation System for e-Learning in Big Data," *Sustainability*, vol. 14, no. 17, pp. 1-22, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[49] Ying Zhang, "Developing an Adaptive Learning Recommendation Algorithm and System for MOOCs," *Journal of Machine and Computing*, vol. 4, no. 4, pp. 962-970, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[50] Nacim Yanes et al., "A Machine Learning-Based Recommender System for Improving Students Learning Experiences," *IEEE Access*, vol. 8, pp. 201218-201235, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[51] Sunil, and M.N. Doja, "An Improved Recommender System for e-Learning Environments to Enhance Learning Capabilities of Learners," *Proceedings of ICETIT 2019: Emerging Trends in Information Technology*, pp. 604-612, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[52] Ipseeta Nanda et al., “ALBERT-Based Personalized Educational Recommender System: Enhancing Students’ Learning Outcomes in Online Learning,” *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 10, pp. 2190-2201, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[53] Mustafa Bin Tariq, and Hafiz Adnan Habib, “A Reinforcement Learning Based Recommendation System to Improve Performance of Students in Outcome Based Education Model,” *IEEE Access*, vol. 12, pp. 36586-36605, 2024. [CrossRef] [Google Scholar] [Publisher Link]