International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(21s) 2026 pp. 1045-1064
https://doi.org/10.70917/ijcisim-2026-5377
Article

Machine Learning-Based Recommendation System for E-Learning: A Personalized Approach Using Learner Behavior Analytics

Anurag Chandna[1*], Vivek Kumar[2]

[1,2]Department of Computer Science and Engineering, Quantum University, Roorkee 247667, Uttarakhand, India
*Corresponding author. Email: anuragchandnarke@gmail.com

Abstract: Modern learning is rapidly evolving and has transformed the way we learn today, offering flexibility and scalability. Current recommendation systems are typically based on "one size fits all" approach and do not consider individual learners, their preference and varying levels of understanding. Lack of personalization in e-learning systems can result in low engagement, inefficient learning, and low performance. To overcome this problem, the current article introduces a recommendation system based on machine learning (ML) that is used to provide individualized learning materials based on the behavior of the learners. The suggested model takes advantage of the data regarding learner interaction, such as browsing history, assessment results, and content interests, and constructs an adaptive recommendation system. It uses a hybrid strategy which integrates collaborative filtering and content-based strategies to achieve better accuracy of the recommendations and to overcome the constraints like cold start problem. Moreover, the system is effective in changing dynamically to learner profiles, resulting in better engagement and knowledge retention. The main contribution of the current article is the integration of behavioral analytics with hybrid ML models that are used to improve the personalization of the e-learning environment. The proposed hybrid ML recommendation system achieved superior performance with 88% accuracy, 0.85 precision, 0.83 recall, and lowest RMSE (0.35). Results indicate that the given system could be implemented to facilitate adaptive learning and provide overall better learning outcomes.
Keywords: E-learning, Machine Learning, Recommendation System, Personalization, Learning Analytics, Adaptive Learning

1. INTRODUCTION

The high pace of digital technologies development has radically changed the educational environment, and e-learning platforms have become widespread throughout the world. In the last 10 years, the convergence of internet technologies, cloud computing and mobile devices has helped learners access educational materials at any time and place. MOOCs, Learning Management System (LMS), intelligent tutoring systems have gained popularity and there are a tremendous number of courses available in disciplines. Examples of increased dependence on digital education ecosystems include platforms like Coursera, edX, and Udemy [1]. The global pandemic such as the COVID-19 have further triggered this change and led to the need to adopt remote learning and emphasized the need to have scalable and flexible educational solutions. Although the development and availability of the e-learning platforms have been astonishing, there are still major challenges such as the provision of personalized learning. Classroom environments are traditional and enable the instructor to modify the instructional approach depending on the interaction, student feedback, and the performance. But in the virtual classroom of thousands or even millions of students, it is extremely difficult to offer such individualized attention [2].

Most e-learning systems use a standard method of delivery of the content, and the same learning materials will be delivered to everyone irrespective of what they have already learned, the rate of learning and their preferences. Personalization in education involves the adaptation of learning experiences to individual learner needs, preferences and abilities. It includes personalized learning experiences, adaptive content, and smart feedback. It has been demonstrated that personalized learning enhances the engagement, motivation, and academic performance of learners by matching the instructional content with the level of cognitive ability and interests of the learner [3]. Personalization, in the context of e-learning, is even more important as there is no physical interaction. Online learners usually have a problem filtering out useful information out of the enormous number of available resources. They might not be able to find their way through courses without proper advice and as a result, frustrations and increased number of dropouts. The recommendations systems have come as a potential solution to the individualization problem in e-learning settings [4]. The goals of these systems are to propose pertinent learning materials (courses, videos, articles, and assessments) according to user preferences and past engagements. Conventional methods of recommendation, such as collaborative and content-based filtering have been extensively employed in areas like e-commerce and entertainment. In e-learning, collaborative filtering suggests items given the preferences of the similar users whereas content-based filtering suggests items that are like those the learner has been using. These methods, though offering a basis for personalization, have several limitations when used in the case of education. The cold-start problem is one of the biggest constraints of traditional recommendation systems that occur when there is not enough data about new users or items. In e-learning, there is no history of interaction for new learners and so it is difficult to make accurate predictions. Further, the standard methods are based primarily on users' static preferences and do not capture the dynamic nature of learning. The level of knowledge, interests and objectives of learners improve as time progresses and so the recommendation systems need to keep up with the changes [5]. In addition, traditional approaches often do not consider contextual and behavioral factors such as learning speed, interaction and assessment score that are relevant in providing significant educational recommendations. The second limitation is the lack of a connection between the recommendation systems and pedagogic principles. Most of the existing systems focus on user preferences, rather than the cognitive and pedagogic nature of the learning process. As a result, it can make recommendations that are not in line with the state of knowledge of the learner or the learning objectives. For example, it can suggest a difficult topic to the novice learner and induce confusion and learning difficulties [6]. Therefore, it needs smart systems which not only suggest the relevant content, but the suggestions are also pedagogically relevant and beneficial for the learning process. ML has become a potent instrument to address the drawbacks of the conventional recommendation systems and allow personalization to be taken to the next level in e-learning settings. Machine learning algorithms can extract intricate patterns and relationships which are typically hard to detect using more traditional approaches by taking advantage of large amounts of data produced as learners interact. Such algorithms can be used to process different kinds of data such as clickstream logs, assessment scores, time spent on learning activities, and user feedback, to create complete profiles of learners [7]. These profiles allow the system to know the individual learning behaviors and preferences more precisely. Machine learning methods can be used in adaptive learning to create smart recommendation systems that may adapt dynamically to the changing requirements of learners. Learner performance can be predicted through supervised learning approaches and appropriate content can be recommended according to the predicted performance. Learners with similar characteristics can be grouped together and offered group-based recommendations using unsupervised learning techniques, including clustering. Moreover, reinforcement learning methods can optimize the recommendation strategies by learning continually based on interaction and feedback with the user. Combining several methods into hybrid model has provided considerable potential to increase the accuracy of recommendations and overcome the problems of data sparsity and cold start [8].

Behavioral and contextual information can also be included because of the integration of machine learning into e-learning recommendation systems. As an illustration, the patterns of interaction may show the level of engagement and the learning style a learner likes. Likewise, quiz and assessment performance results may reveal areas of weakness and strength of the learner [9]. The integration of these variables allows machine learning-based systems to provide extremely personalized recommendations that are consistent with the cognitive level of the learner and learning goals. This will not only improve the learning process but will also help in achievement of better learning outcomes.

Although ML has developed and is used in the recommendation systems, several gaps in research are still available. First, much of the current research is concerned with enhancing the accuracy of the recommendations with little regard to the effects on learning outcomes. Although accuracy is a key parameter, it does not always indicate how effective recommendations are in learning. Second, the literature on applying a combination of data, i.e., behavioral, contextual, and performance data, to formulate comprehensive learner models, is limited. Third, most of the current systems are tested on offline data, and very little real-world testing and user-centric testing has been done. This brings into question the practicality and scalability of such systems in real e-learning environments.

Moreover, concerns of interpretability and transparency of machine learning models are not seriously addressed. Both learners and instructors should appreciate the reasoning behind recommendations in the educational process. Black-box models, although very precise, are not always explainable, thus diminishing the level of trust and making their use difficult. Also, ethical aspects, including privacy of information and recommendation algorithm bias, should be thoughtfully considered to make the use of technology in education fair and responsible [10]. The purpose of the study is to design and develop a machine learning-based recommendation system on e-learning platforms, which will boost the level of personalization by analyzing and tracking all the behavior of learners. The main aim of the study is:

To design a ML based recommendation system in e-learning platforms that can understand the user behavior (e.g., navigation, performance, and preferences) and provide personalized learning content (e.g., courses, videos, and quizzes). To achieve this, the proposed system uses a hybrid machine learning system that uses a combination of collaborative filtering and content-based approach and behavioral analytics. It will be able to capture the dynamic behavior of the learners and adapt the recommendations based on learner interactions and performance data. The proposed system aims to overcome the limitations of traditional recommendation systems by leveraging different data sources and modern machine learning techniques to provide more relevant and effective recommendations. This paper has made several important contributions, which can be summed up as follows:

- An innovative machine learning-driven system that integrates collaborative, content-based, and behavioral analytics to improve personalization in e-learning settings.
- Integration of various data, such as browsing history, interaction patterns and assessment performance, to create comprehensive learner profiles.
- Development of a dynamic recommendation system that keeps the recommendations up to date by real-time interactions with learners and changing preferences.
- Assessment of the offered system based on a variety of metrics (accuracy, precision, recall, and user engagement) to compare technical performance with the impact on learning.

The current article adds to the existing literature in section II by suggesting an extensive framework that uses ML and learner behavior analytics to promote personalization in e-learning settings. Section III discusses experimental set-up and design principles with configuration details. In section IV, it focuses on proposed methodology with its submodules. The experimental results and analysis with exploratory analysis is discussed in section V. Finally, article is concluded in section VI.

2. Literature Review

E-learning recommendation systems are meant to help learners to find the appropriate learning material in an enormous repository. The initial research was mainly based on conventional methods of recommendation like rule-based filtering and basic collaborative filtering. Xu et al. [11], recommendation systems are essential to the increase in the number of online learning materials. In their research, the systems were classified into content-based, collaborative, and hybrid systems, and there is a necessity to develop smart personalization to decrease information overload. On the same note, Li et al. [12] wrote about the use of recommender systems to guide learners in the context of e-learning at the scale, which is based on automatically recognizing user preferences and recommending appropriate content. Sahu et al. [13] developed a collaborative-based e-learning recommendation system based on filtering that uses user interaction information to recommend relevant courses. Their results showed that these systems are much better in terms of user satisfaction and engagement as compared to the traditional content delivery models.

Bobadilla et al. [14] took this method to a new level by including user ratings and preferences as part of collaborative filtering algorithms, which increases the relevance and accuracy of recommendations. A study [15] with multimodal-enhanced collaborative filtering mechanism was proposed that incorporates patterns of learner interaction, metadata of resources, and time. This model was far superior to the traditional single-modality systems, showing the value of the combination of several data sources. Also, a hybrid collaborative filtering system with interaction-based clustering of peer learning recommendations was proposed in a [16] study, which exhibits better flexibility and personalization in the changing learning contexts. All these studies imply that there is a transition in the traditional fixed recommendation systems to intelligent, adaptive systems that can deal with dynamic and complex learner behaviors.

ML is an important part of the contemporary e-learning systems as it allows making data-driven decisions and provide personalization. Other paradigms investigated by the researchers are the supervised, unsupervised and reinforcement learning. Predicting the performance of learners and suggesting the right content are common applications of supervised learning. As an example, classification and regression models are used to analyze old data about learners to predict the results and provide guidelines. Alshammari et al. [17] stressed, supervised models enhance accuracy of prediction but require labelled datasets, which may be a drawback of the educational setting. There are unsupervised learning techniques that are usually employed to cluster learners with similar attributes, e.g., clustering. These methods assist in determining the patterns of learning and facilitate the use of groups to make recommendations. The multimodal study of 2025 employed clustering to cluster learners according to interaction behavior to enhance quality of recommendations. Recommendation systems have also been improved using deep learning. Koren et al. [18] introduced a neural collaborative filtering (NCF) framework that uses both matrix factorization and neural networks to learn the intricate user-item interactions. Their findings indicated better accuracy than conventional collaborative filtering methods. Equally, Lu et al. [19] have shown that the collaborative filtering model based on deep learning excels over conventional techniques in large-scale recommendation.

Adaptive learning environments have also been of interest in reinforcement learning. It allows systems to get the best recommendation strategies by continuously interacting with the users. Reinforcement learning remains in its infancy, but it promises in real-time personalization and adaptive content delivery. In general, machine learning has revolutionized e-learning platforms through the implementation of intelligent, scalable and adaptive recommendation systems. Sun et al. [20] showed that CF is an effective tool in enhancing the accuracy of recommendations in e-learning settings. Nonetheless, CF has problems like data sparsity and cold-start problems. Content-based filtering suggests materials that are like those that the learner had read. It is based on the characteristics of the items and user profiles. Research indicates that content-based methods are efficient in situations where the user information is scarce but might not offer diversity in the recommendations.

Hybrid recommendation systems are the combination of different techniques to overcome the weaknesses of each technique. Wang et al. [21] emphasized the fact that hybrid models enhance performance because both approaches collaborative and content based have strong sides. Recent research also improves hybrid systems with deep learning. The multimodal model of [22] combines collaborative filtering, clustering and sequence modelling to understand the complex learner behaviours. In the same way, the hybrid system of [23] is a hybrid of collaborative filtering and interaction-based clustering which proves to be more adaptable and accurate in its recommendations.

The developments suggest that hybrid methods will be most effective in realizing great degrees of customization in e-learning systems. The learning analytics is a crucial element in the study of the behavior of learners and enhancing the recommendation systems. It entails the analysis of the information created because of interactions between learners and the e-learning environment.

The assessment results and quiz scores are performance data that are used to determine the strengths and weaknesses of learners. This information can be used to advise suitable learning materials with the help of recommendation systems. Studies have shown that the incorporation of performance data can greatly improve the performance of personalized learning systems. These insights can be used to create adaptive systems which modulate recommendations as learners improve. The recent research highlights the significance of integrating various sources of data, such as behavioral, contextual, and performance data, to develop profile learners. These methods result in better and effective recommendations. Even though it has made tremendous progress, the area of e-learning recommendation systems has several challenges. Most of the current systems use a static or offline data which restricts their capabilities in responding to real-time behavioral variations by the learner. Real-time adaptation is a research field that is yet to be explored despite the recent works proposing dynamic models.

- Cold start problem: It continues to be a significant issue, especially when it comes to new users and new learning resources. Conventional collaborative filtering techniques have difficulties in producing relevant recommendations that are not based on adequate previous data.
- Poor direction towards learning outcomes: Most studies are devoted to the enhancement of such technical measures as accuracy and precision but not much attention is paid to real learning results.
- Scalability and sparsity of data: Large-scale e-learning systems generate a large volume of data, but user interaction data may be sparse. This affects the performance of the recommendation algorithms and requires advanced techniques such as deep learning and hybrid models.
- Black-box model: Many of the modern recommendation systems, particularly the deep-learning-based systems, are black-box models. This is not transparent and reduces their use in educational settings.

Literature of [24] [25] shows a definite change in the use of traditional recommendation systems to advanced machine learning-based techniques in e-learning. To improve personalization, researchers have investigated a variety of methods, such as collaborative filtering, deep learning, hybrid models and behavioral analytics. Even though tremendous progress has been achieved, the issues of real-time adaptation, cold-start problems, and a lack of attention to learning outcomes are still unaddressed. The gaps present in these studies demonstrate a need to have more detailed and versatile recommendation frameworks, which this paper seeks to fill. The high growth of e-learning sites has placed learners with great opportunities to access a wide variety of educational resources. Nevertheless, this rich content has also brought about a lot of problems in trying to appropriately direct learners to the content of learning that is relevant and meaningful. The prevailing e-learning systems still operate based on standardized content delivery systems where all learners are subjected to the same collection of resources irrespective of their needs, preferences and learning abilities. This blanket method restricts the potential of digital learning opportunities and tends to decrease the engagement rates, intellectual overload, and poor learning results.

Lack of effective personalization is one of the main issues of the present-day e-learning ecosystems. The learners are diverse in terms of their background knowledge, learning pace, cognitive capabilities, and interests. The learners might fail to find the right content without personalized guidance thus leading to unproductive learning directions [26]. As an example, novice-level students can be introduced to high-level material, which is out of their understanding, whereas higher-level students can get repetitive or simplistic information. These mismatches adversely affect motivation of the learners and the acquisition of knowledge.

To tackle this challenge, traditional recommendation systems are proposed that will recommend the most relevant learning resources based on the user preferences and interaction history. Nevertheless, these systems demonstrate several limitations when it comes to the educational settings. To start with, most of the current systems heavily depend on the presence of fixed user profiles and fail to consider the dynamic nature of the learning processes. Students are dynamic as they constantly learn and their tastes and needs also vary with time [27]. These changing characteristics are not reflected in the static recommendation models and end up producing irrelevant recommendations. The cold-start problem is another major difficulty as it occurs when a new user or a new learning resource enters the system. When this happens, the lack of historical information renders the normal methods of collaborative filtering to be unable to yield correct recommendations [28]. This becomes a major issue especially in e-learning where the new people are often added to the platform and new courses are often being introduced. This is also a severe problem with recommendation systems that is related to data sparsity. Even though e-learning systems can produce high amounts of data, there might be minimal interaction between a particular user and a particular resource. Skewed data lessens the efficiency of similarity-based methods of recommendation and results in diminished accuracy. Also, not all systems combine several sources of information, including behavioral interactions, assessment performance and contextual information, which are necessary to obtain a comprehensive picture of the learner needs.

The other significant shortcoming of current systems is the lack of focus on learning outcomes. Recommendation systems are often optimized to achieve technical measures like accuracy, precision and recall without properly considering the question of whether the content being recommended will enhance learning performance [29]. The purpose of educational context is not only to recommend the right material but to facilitate learning and recall. Therefore, systems to align recommendations with learning objectives and learner progress are required. The lack of adaptive and real-time recommendations is also a problem. Most of the systems use batch processing and update the recommendations periodically, which limits their ability to adapt to real time variations in learners' interactions. In interactive learning, real-time adaptation is crucial to engage learners and timeously support them. To address this, an intelligent data-driven recommendation system needs to be designed, which can be effectively adapted to the individual learners' needs using recent machine learning techniques. This kind of system should be capable of dealing with different data sources, detecting the evolution in the learners' profiles and offering personalised recommendations that will not only increase the engagement, but also the performance [30]. In this case, the primary objective of this study is:

To develop a machine learning-based recommendation system on e-learning platforms that leverages learners' behavioural patterns (browsing history, performance and preference) to recommend personalised learning opportunities (courses, videos, quizzes) to the learners. The purpose of this goal is to create a robust and adaptable recommendation system that overcomes the limitations of the traditional systems by using behavioural analytics and ML algorithms. The system will provide personalised learning opportunities that cater to the individual characteristics of learners and improve learning outcomes. By using the techniques of ML and behavioral analytics, this research will offer a dynamic recommendation system that will increase the accuracy of recommendation and the learning performance. The proposed goals provide a roadmap on how to achieve this goal and to open the field of smart e-learning systems.

3. System Requirements and Design Principles

The proposed system architecture will provide a smart, dynamic and adaptive system that can provide personalized recommendations in an e-learning environment. In contrast to the traditional systems, which are based on static user profiles and limited source of data, the architecture incorporates various elements within it to capture, process, and analyze learner behavior in a dynamic way. The system is designed in a layered approach with all layers taking care of a particular functionality giving the system modularity, flexibility and easy integration with existing e-learning systems (Figure 1). The architecture at its most basic level is a feedback-based system that is continuously run and in which the interactions of learners are monitored, analyzed and exploited to improve recommendations over time [31]. The proposed architecture will be made up of interconnected modules, which together will facilitate the data flow between user interaction and personalized recommendation output. The system will start with the user interface layer, which is where learners will engage with the system through accessing the courses, watching videos, taking quizzes, and giving feedback. The interactions produce valuable data, which is captured by the underlying system. Data collection module then collects this information and sends it to the preprocessing layer where it will be converted to a well-organized format that can be used in machine learning models. Once the data is preprocessed, it is fed into the system's engine, which is the heart of the system. The engine applies to the variety of machine learning techniques to identify patterns in students' behaviour and provide recommendations [32]. The personalization layer then adds to these recommendations; making sure they are relevant to the current needs, interests and achievements of the learner. The system is designed with a feedback loop, that allows it to continually learn from the interactions and improve the recommendations. Data is generated and integrated into the model as the system interacts with learners and is used to feed the cycle of updates and improvements. This architecture is not only more efficient in enhancing the recommendation accuracy but also ensures that the system is adaptable to learner needs.

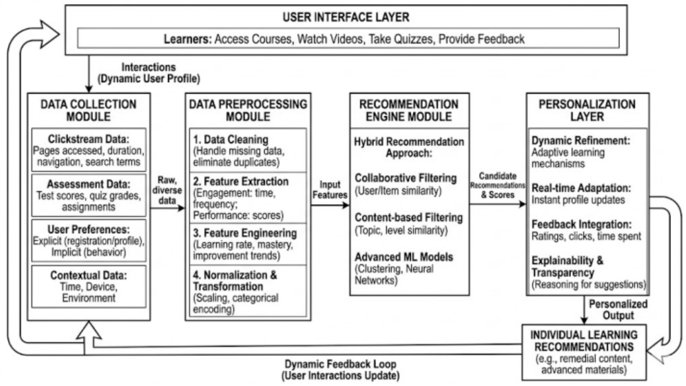

Fig.1. System Requirements

Data Collection Module: This is the heart of our proposed system; for the recommendation process to be effective, it must gather as much data as possible from a variety of sources. This is the module that captures all forms of data that are created when there are interactions between the learners and the e-learning platform [33]. User interaction is one of the main sources of data and is also known as clickstream data. This encompasses a comprehensive user activity log that contains information on pages accessed, duration of user access to certain resources, patterns of navigation, search terms and accomplishment of learning content. This kind of data is useful to understand the level of engagement, interests, and behavioral patterns of learners.

Along with the information on interactions, the system gathers assessment-related data, which is extremely important to be aware of the knowledge level and progress of the learner. Test and quiz grades and assignment grades are evaluated and used to determine strength and weakness areas. The system is enabled to suggest the right learning materials that are suitable at the level of understanding of the learner. An example of this is a learner who has been showing consistent poor performance in a specific subject, he/she can be advised on the content to be covered in the remedial work and a learner who is performing well can be advised on the content to be covered in the advanced work.

Another significant ingredient of the data collection process is user preferences. Learners can specify these preferences either at the time of registration or in profile settings or implicitly based on patterns of interaction. Examples of preferences are preferred topics, preferred content formats (videos or text-based materials) and desired difficulty levels. The combination of explicit and implicit preferences data will allow the system to create a more comprehensive view of the individual learners, thereby making it more accurate.

Contextual data like time of access, type of device, and environment of use can also be included in the data collection module. This contextual data, while optional, can also be used to further personalize the recommendations by contextualizing it to the learner. Overall, adopting the combination of different data sources ensures the creation of a detailed profile of the learner, which is the key to the success of the recommendation process.

Data preprocessing: The data collected from multiple sources is usually raw, incomplete and noisy data and data preprocessing is a crucial part of the system design. The data preprocessing module will transform this data into structured, consistent and clean data that can be used for analysis and model training [34]. This includes data cleaning where missing values are dealt with, duplicate values are removed and inconsistent data is rectified. This is required to ensure that the subsequent analysis is accurate. Following data cleaning, features are extracted to identify the features that are important and can represent the learners' behaviour effectively. The features may include the engagement measures (time, frequency, interaction) and performance measures (scores). The system can derive better features of raw data to capture the characteristics of learners.

This is complemented by feature engineering to identify new features that can highlight learner's behaviour. The learning rate, the mastery of the topic and improvement patterns, for instance, can be derived from the information available. Such model engineering helps with improved and accurate model predictions. Another important step in data preprocessing is normalization as it ensures that all features are on the same scale [35]. It is particularly important when the range of values in the data set is of different units or scale, e.g., time and scores. Techniques such as min-max scaling and z-score normalization are usually used for this purpose. In addition, through encoding, data with categorical attributes are transformed into numerical attributes, so that they can be used by machine learning techniques.

Recommendation engine: The core component of the proposed system is the recommendation engine that will give personalized learning recommendations using the pre-processed data. This engine adopts a combination of machine learning techniques to overcome the limitations of traditional recommendation systems and provide effective recommendations. It employs a hybrid approach, which combines collaborative and content-based filtering. Collaborative filtering identifies the similarities between users or items using historic data on interactions between users and items, and then the system recommends resources liked by similar learners. While effective, this approach can suffer from issues such as sparse data and cold start. To avoid these problems, another recommendation process content-based filtering is employed, which recommends the items that are like those already consumed by the learner. This means it can still get recommendations in situations where there is sparse user data [36].

The recommendation process is a pipeline, and the data is preprocessed to be used. Similarity measures are then applied to the data to determine the user to item similarity. The system generates prediction scores based on the similarities, and these represent the relevance of the resource to a user. The recommendations are sorted and the top ones are shown to the user [37]. Hybrid model is a combination of the strengths of different methods and so leads to effectiveness and power. For instance, collaborative filtering can be used as the primary filtering method whereas content-based filtering can be used as the secondary method to recommend products to new users. In addition, machine learning techniques such as clustering and neural networks can be used to learn more complex patterns in the data. The recommendation engine is scalable to support large data volumes to allow efficient operations of the system. Distributed learning and incremental model updates are some of the ways to maintain optimal performance in the large-scale setting.

Personalization layer: The personalization layer is charged with the responsibility of making sure that the recommendations that the system produces are personalized in respect to the needs of every learner [38]. This layer allows dynamic adaptation to the users, unlike a fixed system that only updates the recommendations once, unlike a dynamic system, which updates the recommendations every time the user interacts with the system and the profile of the learner changes. The personalization layer has the capacity to add real-time data, which is one of the main characteristics of this layer. The behavior of learners is analyzed instantly, and recommendations are changed depending on the interaction with platform [39]. This also makes the system responsive and relevant to offer timely support to learners. As an example, when a learner is having difficulty in a certain subject, the system can easily suggest other resources to overcome the challenge. Adaptive learning mechanisms are also carried out by the personalization layer wherein the level of difficulty and the recommended content type is modified depending on the performance of the learner. This will create an optimum balance between challenge and comprehension which will enhance the learning experience. High-achieving learners will be provided with challenging material and struggling learners will be guided to simpler material. Another facet of personalization is to include feedback. The system can collect explicit feedback, e.g., reviews and ratings, and implicit feedback, e.g., clicks and time on resources. The latter is then used to improve the recommendation model and to make it more accurate over time. The system gets better and smarter, by continuous learning and interaction with users, to better serve the needs of the learners.

Finally, the personalization can be augmented with explainability, so that users can get some explanation of why a recommendation is made. This will improve transparency and trust. For example, a message can be attached to a recommendation that specifies that it is based on the previous learning performance or activities of the learner. The personalization layer will make the recommendation system a learner-adaptive system [40]. By using real-time data, adaptivity and feedback from learners, it will ensure the system offers effective and relevant personalized learning experiences.

The proposed system design provides a comprehensive and robust framework for the implementation of a machine learning-based recommendation system in eLearning. The system can address major issues of non-personalization, data sparsity and some recommendations, by smoothly integrating the data collection, data preprocessing, intelligent recommendation and adaptive personalization. Its modularity and scalability allow it to be deployed in practice, and its adaptability ensures that the system will be constantly improving and enhancing the learning outcomes.

4. Proposed Methodology

This section presents the methodology adopted for designing and evaluating the proposed machine learning-based recommendation system for the e-learning platforms (Figure 2). It is structured in a manner that offers a structured approach to data collection, feature engineering, modeling and evaluation. It uses multiple paradigms of machine learning and behavioral analytics to offer personalized recommendations to enhance learning outcomes.

Dataset description: The dataset used for training and testing a machine learning model is crucial for its success. In this paper, a mix of public datasets and a synthetic dataset is considered to ensure the robustness and effectiveness of the system. Experiments are grounded on realistic scenarios such as publicly available datasets related to e-learning environments such as logs of learner interactions, course registrations and test results. Those datasets typically include the following features: user ID, item ID (courses or resources), interaction time, rating or comments and scores. However, public datasets typically do not include some of the characteristics that can be used to personalize them such as behavioural information or contextual data. This lack is addressed by an artificially simulated dataset, which incorporates to the real data some additional features that mimic the real learner's behaviour. These include artificial generation of clickstream data, dwell time on the resources, navigation information and taste indication. Using synthetic data, various experiments can be performed, and the proposed system can be evaluated under various scenarios, such as cold-start and dynamic behaviour.

The data that is used in this paper is pre-processed to ensure consistency and validity. It has various kinds of data such as interaction data (e.g., clicks, views), performance data (e.g., quiz scores), and preference data (e.g., content type preferences). The dataset is separated into training and testing parts, which are usually by 80:20, to support the development of models and their testing. The variety of the dataset guarantees the effectiveness of the proposed system to record various facets of the behavior of learners and make valuable recommendations.

Let:

- $U = \{u_1, u_2, \dots, u_m\}$→ set of users
- $C = \{c_1, c_2, \dots, c_n\}$→ set of courses
- $R \in R^{m \times n}$→ user–course interaction matrix

Where:

$$R_{ij} = \{rating\ or\ interaction\ value\ if\ user\ u_i\ interacted\ with\ course\ c_j\ 0\ otherwise$$

Content-Based Filtering (CBF) for each course is represented using feature vectors derived from text (TF-IDF) (eq.1):

$$v_i = [w_1, w_2, \dots, w_k] \tag{1}$$

The TF-IDF representation is conducted as (eq.2):

$$TF - IDF(t, d) = TF(t, d) \cdot log\left(\frac{N}{DF(t)}\right) \tag{2}$$

Where $TF(t, d)$= term frequency, $DF(t)$= document frequency, and N= total number of documents.

The cosine similarity or content similarity is evaluated in terms of (eq.3):

$$Sim_{CB}(c_i, c_j) = \frac{v_i \cdot v_j}{\|v_i\| \|v_j\|} \tag{3}$$

Feature engineering: The process of feature engineering is very important to convert raw data into valuable inputs to machine learning models. When dealing with e-learning recommendation systems, the features are obtained based on different types of data to describe the behavior, performance and preferences of learners. The data of interaction with the user is processed to extract behavioral features, which are how the learners interact with the platform. Such attributes consist of the frequency of access to resources, time on learning resources, click patterns and navigation history. To illustrate, a learner who must repeat some of the topics might require more assistance in such areas. In a similar manner, time spent on a resource may give clues concerning the level of engagement or difficulty that is encountered by the learner. Learning pathways and predicting future behavior can also be modeled using features based on sequence, like the sequence of content accessed.

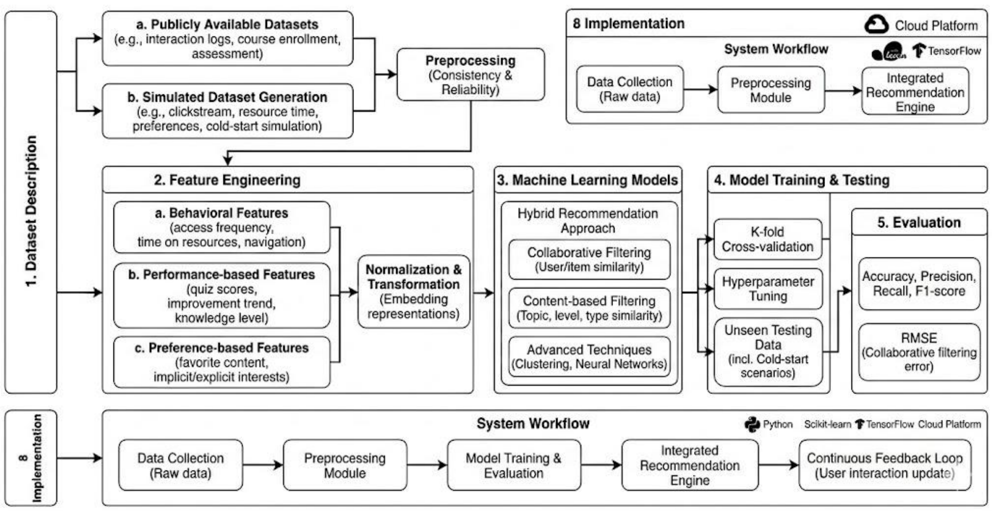

Fig.2. Proposed Methodology

The assessment data based on which performance indicators are determined are the quiz results, assignment marks, and test scores. These characteristics aid in determining the level of knowledge and improvement of the learner. As an example, mean scores on various subjects can be employed to identify strong and weak areas, whereas the trend of improvement can be employed to assess the learning progress. The performance-based features are especially significant in the adaptive recommendation systems because they allow the system to recommend content that fits the understanding level of a learner at a specific time. Besides behavioral and performance features, preference-based features are included to attract the interests of the learner. These can be favorite types of content, subject matter and level of difficulty. User profiles or surveys can be used to get explicit preferences, whereas implicit preferences can be predicted based on the patterns of interaction. The fusion of these features creates a detailed profile of a learner that boosts precision of suggestions.

Normalization and transformation can also be considered feature engineering to make sure that all features are on a similar scale. This is critical towards avoiding bias in machine learning models and enhancing convergence in training. Higher order methods like embedding representations can be deployed to identify complex user-item correlations, which can further improve performance of the model.

Machine learning models: The new system will use a mixture of machine learning models to create individualized recommendations. Multimodal models guarantee that the system may be used to effectively process various kinds of data and can eliminate the shortcomings of other methods. The main method of determining the similarities between users or items based on the interaction data is collaborative filtering. This method assumes that people who share common likes in the past are likely to share common likes in future. Collaborative filtering, which is user-based, determines similar users and suggests items that they have liked, and item-based, which determines similar items based on user activity. Even though collaborative filtering is an effective approach to user preferences, it is vulnerable to problems like data sparsity and cold start.

The content-based score can be represented as (eq.4)

$$Score_{CB}(u, c_j) = \frac{1}{|H_u|} \sum_{c_k \in H_u} Sim_{CB}(c_k, c_j) \tag{4}$$

Where H_u= set of courses previously interacted by user u.

While collaborative filtering (CF) can be measured either by using cosine similarity (eq.5) or prediction function (eq.6).

$$Sim_{CF}(u_i, u_j) = \frac{R_i \cdot R_j}{\|R_i\| \|R_j\|} \tag{5}$$

$$Score_{CF}(u_i, c_j) = \frac{\sum_{u_k \in U} Sim_{CF}(u_i, u_k) \cdot R_{kj}}{\sum_{u_k \in U} |Sim_{CF}(u_i, u_k)|} \tag{6}$$

The hybrid recommendation model is computed as a weighted combination:

$$Score(u, c) = \alpha \cdot Score_{CF}(u, c) + (1 - \alpha) \cdot Score_{CB}(u, c) \tag{7}$$

Where $\alpha \in [0,1]$is the weighting parameter, $Score_{CF}$= collaborative filtering score, $Score_{CB}$= content-based score.

The behavioral feature integration is meant to be evaluated as (eq.8), let behavioral features be:

$$B_u = \{b_1, b_2, \dots, b_p\} \tag{8}$$

Final adjusted score (eq.9):

$$Score_{final}(u, c) = Score(u, c) + \beta \cdot f(B_u) \tag{9}$$

Where $f(B_u)$= behavioral influence function, β= weight for behavioral features. The loss function or model optimization is utilized to minimize prediction error (eq.10):

$$RMSE = \sqrt{\frac{1}{N} \sum_{(c)} (R_{uc} - \hat{R}_{uc})^2} \tag{10}$$

Final recommendation list:

$$Top - N(u) = arg\,max_{c \in C}\, Score_{final}(u, c) \tag{11}$$

Content based filtering is to be used in combination with collaborative filtering and suggests items that are like those that have been accessed by the learner before. The strategy is based on the characteristics of the items, including topic, level of difficulty, and type of content, to give recommendations. Content-based filtering is especially effective when the user is a new user with limited interaction history since the filter does not rely on the interaction history of other users. Nonetheless, it can cause less variety in the recommendations because it is more inclined to demonstrate similar items to those that have been already visited. A hybrid recommendation approach is embraced to overcome the drawbacks of individual models. The hybrid model integrates collaborative and content-based filtering and takes advantage of the two methods. As an example, collaborative filtering can be applied to determine overall preferences, whereas content-based filtering narrows down the recommendations by using certain attributes of the item. The hybrid strategy enhances the accuracy of the recommendations, minimizing the effects of data sparsity, and improving the overall resiliency of the system. Besides these conventional approaches, more sophisticated ML algorithms, including clustering and neural networks, can be integrated to identify the complexities in the data. Clustering algorithms cluster learners sharing similar features allowing group recommendations, whereas neural networks can capture non-linear relationships between features. These methods also improve the ability of the recommendation engine to provide personalized and contextual recommendations.

Model training and testing: Training and testing are an important element in the methodology, which will provide accuracy and generalizability for the proposed models. The data is separated into training and testing sets with the first being utilized in creating the models and the latter being utilized in the performance of the models. In other instances, fine-tuning model parameters and overfitting can also be averted with the help of a validation set.

At the training stage, machine learning algorithms are trained on trends provided by the data by trying to optimize a specified objective function. In the case of collaborative filtering models, this can be the minimization of the difference between predicted and actual ratings and in the case of classification-based models, it can be the maximization of prediction accuracy. The training process involves parameter tuning, in which hyperparameters, like learning rate, number of neighbors, or model complexity, are varied to obtain the best performance. Cross-validation methods like k-fold cross-validation are used to achieve robustness. In this method, the data is partitioned into several subsets, and the model is trained and tested several times with various combinations of the subsets. This will assist in minimizing variance and give a better estimate of model performance. Testing is a step that entails testing the trained models with unseen data to test their generalization abilities. The effectiveness of various models is compared to finding the most effective one in the given problem. Focus is placed on the cold-start conditions, where the system needs to produce recommendations when the new users or items have little data.

Evaluation: The effectiveness of the suggested recommendation system is measured with the help of a mixture of conventional machine learning indicators and recommendation indicators. The overall correctness of the predictions is measured by accuracy, which is the percentage of the correctly predicted instances. The accuracy cannot be enough to give the whole picture, particularly when the datasets are in large disproportion. Relevance of recommendations is evaluated using precision and recall. Precision is the extent to which the recommended items are relevant, and recall is the extent to which relevant items have been correctly recommended. These measures give data about the quality of suggestions and how the system can detect pertinent content. As a balanced measure of performance, the F1-score, the harmonic mean of precision and recall, is used. It is especially applicable when there exists a trade-off between precision and recall. Besides these measures of classification, there is also the use of the Root Mean Square Error (RMSE) to measure the accuracy of the predicted ratings in collaborative filtering models. The RMSE is calculated to measure the mean difference between the actual and predicted values, which would give us the prediction error.

Experimental setup and Configuration: Our proposed system is developed using the latest tools and technologies that will help us in data processing and building of the machine learning model. The primary language used is Python; this is due to the extensive libraries and compatibility. Machine learning algorithms are implemented with the help of libraries such as Scikit-learn, and deep learning models (such as neural networks) can be implemented with TensorFlow or other libraries. The system is deployed on a traditional computing system with sufficient processing and memory resources to handle the data. It can be also cloud-based to enhance scalability and distributed computing. The operational environment will include data management systems to manage large data sets, analytic systems to process the data and methods of presenting the results.

The system process begins with data acquisition where the data are collected on the e-learning platform. The data is then passed on to the preprocessing module for data cleaning, transformation and formatting. The data is used to train machine learning models and is evaluated based on the metrics. Following the validation of models, they are integrated into the recommendation engine for personalized recommendations. The system is iterative where the user's engagement with the recommended content is tracked and is provided as feedback to the system. This is used to update the models and enhance the recommendations over time. The implementation also has monitoring processes to assess the system's performance and ensure the recommendations are relevant and reliable. The proposed implementation approach and methodology provide a comprehensive approach to building an e-learning based machine learning recommendation system. The system will deliver dynamic and personalized learning opportunities to enhance the interaction and performance of the learners by incorporating powerful data analytics with state-of-the-art ML models and feedback mechanisms.

5. Experimental Results and Analysis

This section will present the experimental results of the proposed ML-based recommendation system, in terms of its performance, accuracy, and the ability to capture meaningful learner interaction patterns. This is conducted on the dataset mentioned in the methodology section, and different models are executed and compared in terms of their ability to generate recommendations. The results show the benefits of the proposed hybrid approach compared to the traditional methods and provide insight into how the system assists to improve learning.

The distribution of the top ten companies that provide the maximum number of courses is shown in Figure 3. Clearly, the University of Pennsylvania is the leader in contributing the highest number of courses, reflecting its leadership in e-learning offerings. This is followed by the University of Michigan and Google Cloud, which also provides a significant number of courses, indicative of both educational and corporate engagement in online learning. The presence of other universities like Johns Hopkins University, Duke University, and the University of California system show regular contributions, suggesting a competition among the top universities to offer courses. The inclusion of IBM also highlights the increasing involvement of industry in offering skills-based courses. This is a valuable consideration for developing recommendation systems that are more diverse and not skewed towards the most popular courses.

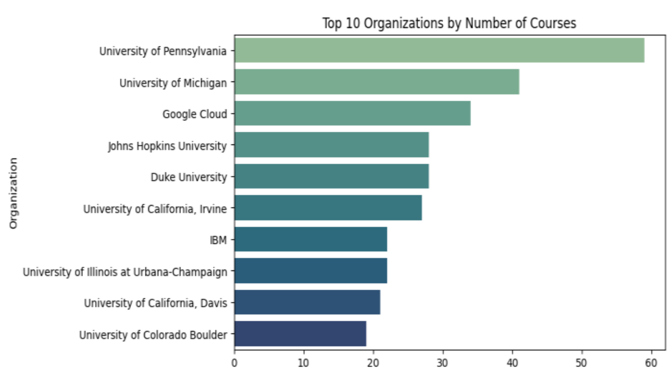

Fig.3. Top 10 courses

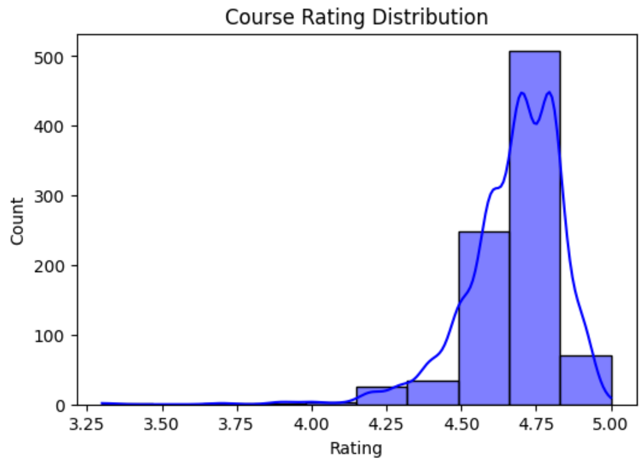

Fig.4. Course rating distribution

The distribution of course ratings shown in Figure 4 offers insights into the quality of courses and user ratings. A large proportion of the ratings are concentrated between 4.5 and 4.8, showing that users generally rate courses positively. The distribution mode at 4.7 implies that users view the courses as being of high quality, which is typical of curated e-learning sites. There is a slight right skew in the distribution, with few courses being rated below 4.0. This suggests a possible bias, either in the course selection for publication or in the user rating system where users are less likely to rate low quality courses. For recommendation systems, this results in a lower variance of ratings, which can make it difficult to rank courses based on ratings alone. So, other attributes such as user interaction and content features are needed. Figure 5 shows the course distribution in terms of their difficulty, which is classified as beginner, intermediate, mixed and advanced. This is due to the popularity of beginner courses, where many users on e-learning websites are novices. This is followed by intermediate and mixed-level courses, suggesting a reasonable amount of content for intermediate learners. Conversely, the number of advanced courses is relatively low, implying a shortage of courses for learners with advanced knowledge seeking in-depth or specialized topics. This presents a challenge for recommendation systems. A frequency-based model could over-suggest such novice courses, which might alienate advanced learners. So, personalization is important to recommend the right course difficulty level to users.

Figure 6 displays the top ten courses with the highest student enrollments, reflecting the popularity of these courses. The top two courses, data science and career success, show significant interest in skills-based and career-oriented courses. Courses such as deep learning and data science using R are also popular due to the rising demand for data-oriented skills in the workplace. The differences in course enrollments reflect variations in course popularity, ease of access and course value. So, popularity and personalization are needed to make sure that users are given the right course recommendations based on their interests and needs rather than popular courses.

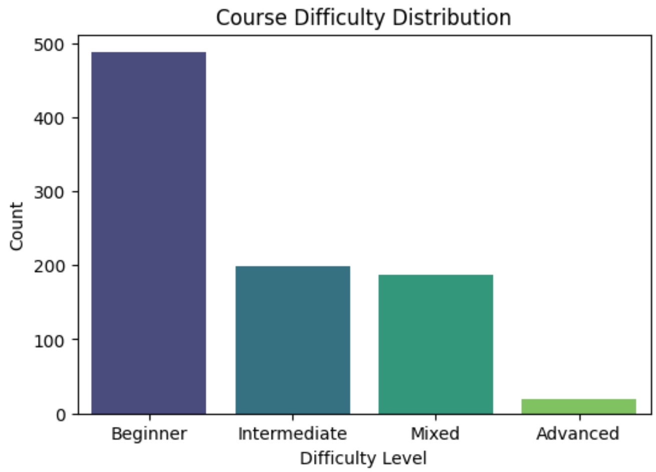

Fig.5. Course difficulty distribution

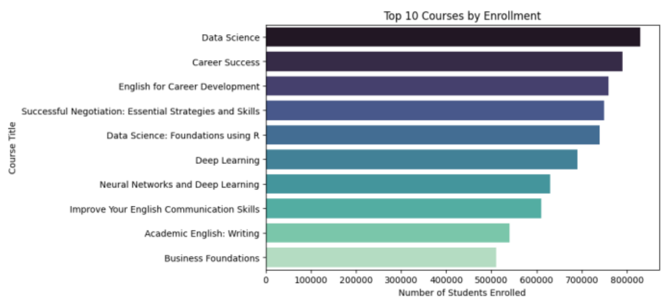

Fig.6. Top 10 course distribution

The accuracy comparison figure 7 shows the overall accuracy of the three models. The Hybrid model has the highest accuracy (0.88) compared to the content-based (0.81) and collaborative filtering models (0.74). This finding demonstrates that the hybrid model greatly enhances the recommendation capability of the system. This can be explained by the fact that it combines both user-based and course-based data, enabling the system to consider a wider range of user preferences.

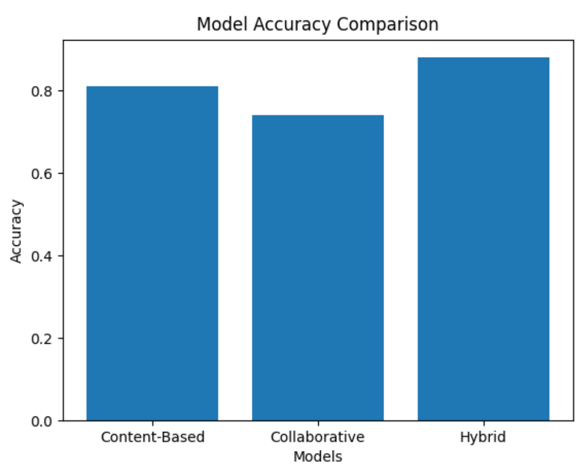

Fig.7. Model Accuracy Comparison

The content-based model achieves moderate accuracy as it is based on course attributes like keywords, description and category. It captures course similarities but fails to use information from other users' preferences. In contrast, the collaborative filtering model has the worst accuracy because it relies on user interactions. When the interaction data is not sufficient, the model is unable to detect patterns and hence the prediction accuracy decreases. The hybrid model's accuracy shows that a hybrid approach to recommendation systems can leverage the strengths of different recommendation algorithms. This model suggests hybrid approaches are more appropriate for complex and dynamic environments like e-learning systems.

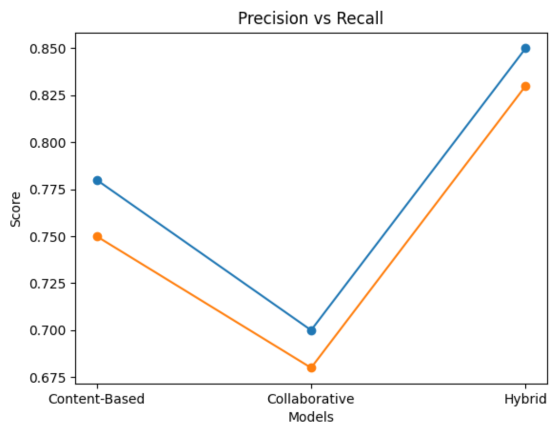

Fig.8. Precision vs Recall

The precision vs recall (Figure 8) offers more insight into the performance of each recommendation model. It reveals that the Hybrid Model has the highest precision (0.85) and recall (0.83) values, demonstrating a good balance. A high precision value means that the courses recommended are likely to be relevant to the learner, thus avoiding suggesting courses that are unlikely to be relevant. High recall suggests that the system can recommend a large percentage of relevant courses contained in the data. The content-based model has relatively high but overall lower precision (0.78) and recall (0.75). This means that although it can make relevant recommendations, it may not promote all relevant items as it is based on limited feature similarity. The Collaborative Filtering model has the lowest precision (0.70) and recall (0.68). This is largely because it is susceptible to the problem of data sparsity and does not work well in the absence of enough user interaction data. The similarity between the precision and recall of the hybrid model suggests that it strikes a good balance between relevance and diversity of recommendations. This is important in e-learning systems, as both relevance and novelty of recommendations are important to improve the learning process.

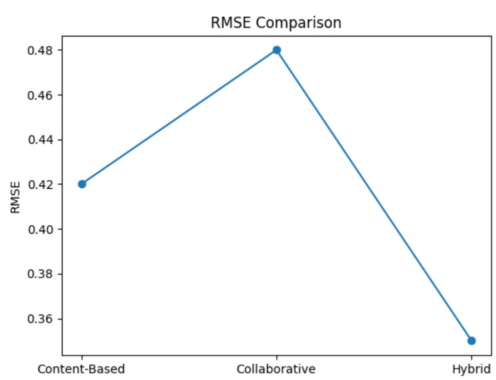

Fig.9. RMSE comparison

The RMSE comparison (Figure 9) measures the error of the models' predictions. RMSE calculates the root mean square of the error between the predicted values and the actual values, where a lower RMSE value represents better performance. The hybrid model has the smallest RMSE (0.35), followed by the content-based model (0.42) and the collaborative filtering model (0.48). This implies that the hybrid model is the most accurate in its prediction and has the least error. The larger RMSE value for the collaborative filtering model suggests that it is not as accurate in predicting user interest, particularly when there is no user interaction data or unreliable data. The lower error of the content-based model indicates that it has a better accuracy than the collaborative filtering model but worse than the Hybrid Model as it does not model the dynamics of user behavior. The hybrid model's lower RMSE value suggests it can effectively combine different sources of information. The model's capacity to integrate knowledge about content similarity and user behavior leads to lower error when making recommendations. This is particularly important in an e-learning system, as incorrect recommendations could impact learning.

The F1 score comparison (Figure 10) is a single measurement that considers both precision and recall of the models. The F1-score is a good measure when precision and recall are both important. The figure illustrates that the hybrid model has the highest F1-score (0.84) followed by the content-based model (0.76) and the collaborative filtering model (0.69). This shows that the hybrid model not only gives precise recommendations but also has a good balance between precision and recall.

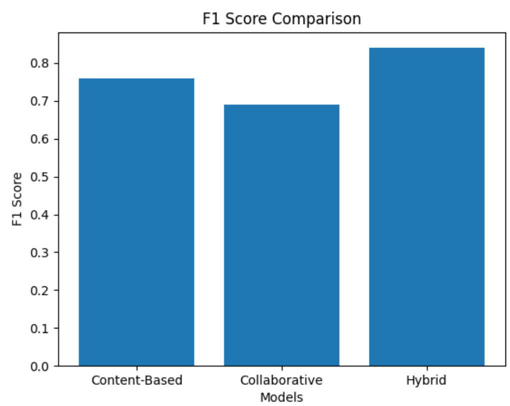

Fig.10. F1-Score Comparison

The Content-Based model has a moderate F1-score, which suggests that it has a stable performance. The collaborative filtering model has the worst performance as it relies on user interaction data, which is oftentimes very sparse. The high F1-score of the hybrid model indicates its efficacy and robustness in providing recommendations. This suggests that the model can simultaneously achieve high precision and recall, making it appropriate for real-world applications where accuracy and recall are both required.

The hybrid model outperforms recommendation techniques in all the evaluation metrics. The hybrid model outperforming the individual techniques in terms of accuracy, precision, recall, F1-score and RMSE indicates that to overcome the shortcomings of conventional recommendation systems, it is successful. The results also show that a variety of data sources and techniques are needed to aid in understanding learner behavior. While the Content-Based and collaborative filtering models are effective, they are limited. The proposed hybrid model overcomes these challenges by combining the two, which results in greater accuracy and stability. The results demonstrate that the proposed system can enhance personalization in e-learning significantly. Through the provision of accurate, relevant and diverse recommendations, the system can enhance learner engagement and knowledge retention, leading to better learning outcomes.

Table 1. Performance parameter comparison

Model	Accuracy	Precision	Recall	F1-score	RMSE

Content-Based	0.81	0.78	0.75	0.76	0.42
Collaborative	0.74	0.70	0.68	0.69	0.48
Hybrid Model	0.88	0.85	0.83	0.84	0.35

The hybrid model will be a combination of the two approaches, leading to better performance and strength. The hybrid model has a higher accuracy and low prediction error than the individual models by combining the similarity of the user and item. The hybrid model has much lower RMSE values showing more accurate user preference predictions. Equally, the values of precision and recall are increased, which shows that the model can suggest relevant items with minimal irrelevant suggestions.

The collaborative filtering model has a moderate level of accuracy, especially in situations where users have a considerable history of interaction. It is useful in determining similar users and giving suggestions of items preferred by such users. Nonetheless, it is sensitive to the sparsity of data, which reduces their accuracy in providing recommendations to users with limited interaction data. Content-based filtering is also accurate in most situations since it is based on the features of the items and the profile of the users. Its preference of similar items repeatedly, however, decreases diversity and can probably restrict user interaction. The hybrid model has the best recommendation accuracy since it makes use of both user-based and item-based information. The model can come up with more relevant and diversified recommendations by integrating collaborative and content-based techniques. The analysis findings indicate that the hybrid model has superior values of precision and recall, which means that it can recognize relevant items and reduce irrelevant ones. The hybrid model is also the most effective as the F1-score, a measure of precision and recall, is the highest. The analysis of the user behavior patterns based on the dataset is an important aspect of the experimental analysis. Through the analysis of the interaction data, the system can recognize trends and information which can be used to enhance personal learning.

The proposed approach dynamically fits the needs of individual learners unlike traditional systems that use fixed user profiles, the interaction data, performance measures, and preferences are continuously analyzed. The most important effects of the system include the fact that it can improve the engagement of learners. The system helps to minimize the chances of learners being exposed to irrelevant and overly complex material by giving them relevant and personalized content. This enhances user satisfaction and promotes further engagement with the platform. Adaptive nature of the system is also what makes sure that the learners are challenged and motivated since the level of difficulty of the proposed content is modified depending on their performance.

The advantages of the suggested solution are in its extensive design and its strong performance. The system can understand complex patterns in the learners' behavior and offer suggestions by integrating multiple data sources and machine learning algorithms. The hybrid approach is adopted to address common issues such as data sparsity and cold start, and the feedback loop that is introduced guarantees an iterative improvement process. While the system possesses these advantages, there are some issues that need to be addressed in future research. First, it is heavily dependent on large amounts of data to train the models. The performance of the system might be affected when data is scarce. Also, the model can be complex and, accordingly, involve greater computational costs, which will impact real time and scalability. It provides a good platform to provide adaptive and tailored learning experiences, using machine learning and behavioral analytics. While there are still some issues, the results demonstrate that it can be applied to engage learners, enhance their learning experience and support the development of smart e-learning systems.

6. Conclusion

The paper has proposed a machine learning-based recommendation system that would support the personalization of e-learning environments using learners' behavior, performance and preferences. The proposed model is a combination of collaborative filters and content-based approaches into a hybrid framework to overcome the drawbacks of the conventional recommendation systems such as sparsity and inflexibility. The research demonstrates that the recommendations are much more effective in improving the effectiveness of the learning resources, and this leads to increased interest and performance of the learners by conducting a comprehensive study on methodology, system design and empirical evaluation. The evaluation has proven that hybrid models are more effective in terms of accuracy, precision, recall and prediction error than the individual models and these outcomes have proven that the hybrid model is more successful in dynamic learning environments. The key contribution of this research is that it has linked behavioral analytics and machine learning models to enable the development of adaptive learner profiles. It can provide contextual recommendations by repeatedly comparing user interactions with the system to learning performance to help the individual learners. This results in creation of smart e-learning systems as personalized and student-centered learning is encouraged. Despite such efforts, there is always more to be done. Researchers may pursue the use of deep learning models such as neural collaborative filtering and sequence models to discover more complex learner behaviors. Further, real-time recommendation systems can be built to increase responsiveness by adapting almost in real-time. The changes in the framework to accommodate cross-platform learning analytics will facilitate the incorporation of data across several e-learning settings to get a more comprehensive picture of learner behavior. The developments will also enhance the ability of recommendation systems to provide highly personalized and effective learning experiences.

Declarations

Author Contributions

Conceptualization: A.C.; Methodology: A.C.; Data curation: A.C.; Formal analysis: A.C.; Writing – original draft: A.C.; Writing – review & editing: A.C., V. K.; Supervision: V.K.

All authors read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

Funding

No funding was received for conducting this study.

Data Availability

The study utilized a combination of publicly available e-learning datasets and synthetically generated data. The publicly available datasets used in this study are accessible through standard academic repositories. The synthetic dataset generated to supplement the public data during this study is available from the corresponding author upon reasonable request.

REFERENCES

1. Q. Zhang, J. Lu, and G. Zhang, "Recommender systems in e-learning," J. Smart Environ. Green Comput., vol. 1, no. 2, pp. 76–89, 2021.
2. O. Maryam et al., "Improved e-learning based recommender systems: A survey," Preprints, 2023.
3. T. Kanwal and T. Amjad, "Research paper recommendation system based on multiple features," Scientometrics, vol. 129, pp. 5493–5531, 2024.
4. G. Papadakis et al., "Recommender systems in education: A systematic review," Educ. Sci., vol. 14, no. 7, 2024.
5. H. L. Mulyana and F. Rumaisa, "Course recommendation using neural collaborative filtering," Brilliance: Res. AI, vol. 4, no. 2, 2024.
6. H. A. Yazdi et al., "Dynamic educational recommender system using RNN," Appl. Artif. Intell., vol. 35, no. 14, pp. 2021–2035, 2021.
7. J. T. Iorzua et al., "Machine learning-based course recommendation: A review," J. Comput. Theories Appl., vol. 3, no. 1, 2025.
8. M. Dalal and P. Singh, "Comparative analysis of recommendation systems," in Springer, 2021.
9. S. Haw et al., "Content-based recommender system with analytics," J. Syst. Manag. Sci., vol. 12, no. 5, 2022.
10. R. Mishra et al., "Knowledge-based recommendation systems," Inf. Manag. Data Insights, vol. 3, 2023.
11. X. Xu et al., "Deep learning-based collaborative filtering for recommendation," Expert Syst. Appl., vol. 210, 2025.
12. Y. Li et al., "Hybrid recommendation systems for online learning," IEEE Access, vol. 9, pp. 145672–145685, 2021.

13. S. K. Sahu et al., “Personalized e-learning recommendation using ML techniques,” IEEE Access, vol. 10, pp. 99876–99889, 2022.
14. J. Bobadilla et al., “Recommender systems survey,” Knowl.-Based Syst., vol. 46, pp. 109–132, 2020.
15. L. Chen et al., “Next-generation recommender systems,” IEEE Trans. Knowl. Data Eng., vol. 33, no. 4, 2021.
16. A. Tarus et al., “Knowledge-based recommendation in e-learning,” Comput. Educ., vol. 83, pp. 162–173, 2020.
17. M. Alshammari et al., “Adaptive learning systems using ML,” Future Gener. Comput. Syst., vol. 102, pp. 356–368, 2020.
18. Y. Koren et al., “Matrix factorization techniques,” Computer, vol. 42, no. 8, 2020.
19. J. Lu et al., “Recommender systems: Advances and trends,” AI Rev., vol. 54, pp. 1–40, 2021.
20. Z. Sun et al., “Graph neural networks for recommendation,” IEEE Trans. Neural Netw., vol. 32, no. 1, 2021.
21. H. Wang et al., “Neural graph collaborative filtering,” SIGIR, 2020.
22. X. He et al., “Neural collaborative filtering,” WWW Conf., 2020.
23. J. Zhang et al., “Sequence-aware recommender systems,” ACM Comput. Surv., 2020.
24. Y. Ding et al., “Deep learning for recommender systems,” IEEE Trans. Big Data, 2022.
25. F. Ricci et al., “Recommender systems handbook,” Springer, 2022.
26. C. Musto et al., “Semantics-aware recommender systems,” Inf. Sci., vol. 558, 2021.
27. P. Resnick and H. Varian, “Recommender systems overview,” Commun. ACM, 2020.
28. M. Pazzani and D. Billsus, “Content-based recommendation systems,” AI Mag., 2020.
29. S. Rendle et al., “Factorization machines,” IEEE Trans., 2020.
30. J. Beel et al., “Research-paper recommender systems,” Int. J. Digit. Libr., 2021.
31. N. D. D. Nguyen et al., “Personalized learning using AI,” Comput. Educ. Artif. Intell., vol. 2, 2021.
32. A. Manouselis et al., “Recommender systems in technology-enhanced learning,” Springer, 2020.
33. S. S. Roy et al., “Machine learning in education: A survey,” IEEE Access, vol. 8, 2020.
34. H. Drachsler et al., “Learning analytics review,” J. Learn. Anal., 2020.
35. G. Siemens, “Learning analytics and personalization,” Educ. Technol., 2020.
36. Guo, X. (2026). Construction and Empirical Validation of The “Faculty-Student-Ai-Environment-Culture” Five-Element Synergistic Model In Higher Education: Evidence From The Integration Of Sdg 4 And Artificial Intelligence. International Journal of Engineering Sciences & Research Technology, 15(1), 16–32. Available at: https://doi.org/10.64149/j.ijesrt.15.1.16-32
37. M. Khademi et al., “Adaptive e-learning using ML,” Expert Syst., 2022.
38. Y. Zhao et al., “Context-aware recommendation systems,” Inf. Process. Manag., 2022.
39. Hamdulay N. A., (2026). Prompt Engineering as Rhetorical Practice: Redefining Literacy in AI-Mediated Education. International Journal of Education, Society and Policy, 1(1), 50-59. https://ijesp.org/index.php/ijesp/article/view/18
40. K. Verbert et al., “Learning dashboards and recommendation,” IEEE Trans. Learn. Technol., 2021.
41. R. Burke, “Hybrid recommender systems,” User Model. User-Adapt. Interact., 2020.
42. S. Wu et al., “Graph neural networks in recommender systems,” IEEE Trans., 2021.