

Literature Review on Course Recommendation System for Personalized E-learning

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Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

E-learning sites have revolutionized education by providing accessible, flexible and personalised learning opportunities to students in all parts of the globe. Nevertheless, the sheer amount of online courses and educational resources in the modern world usually leads to the meaning of cognitive load, as a learner cannot find the resources that suit his/her needs, interests, and learning objectives the most. In a bid to overcome this challenge, E-learning Recommendation Systems (ERS) has become a significant area of research in an endeavor to increase the personalization, enhance the learning engagement and facilitating the adaptive learning environments. This review paper will focus on the current developments, techniques, and trends in E-learning recommendation systems and the way different strategies such as content-based filtering, collaborative filtering, hybrid models, semantic-based recommendations, and deep-learning-driven frameworks can influence the accuracy and satisfaction of the recommendation. According to the review, the main merits of the current approaches include personalization and flexibility, although severe limitations, including cold-start issues, scarcity of data, insufficient contextual awareness, and a lack of semantic meaning, are also noted. Also, this paper explains the manner in which the existing systems combine behavior of the learner, preferences, history of his or her performance, and contextual information to provide valuable advice. The review ends with the conclusion that recommends the growing significance of smart, scalable, and context-effective recommendation models as a part of the future of digital education. It also points out the possible opportunities of research such as emotion-sensitive systems, graphical-based learning, reinforcement learning methods, and privacy-sensitive architectures which can also enhance personalized learning in E-learning ecosystems.

Keywords: E-learning, Recommendation Systems, Personalization, Machine Learning, Deep Learning, Hybrid Models, Adaptive Learning, Educational Technology.

How to cite this article: Garg A, Babu MS. Literature Review on Course Recommendation System for Personalized E-learning. *Int J Drug Deliv Technol.* 2026;16(34s):496-501. DOI: 10.25258/ijddt.16.34s.65

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

INTRODUCTION

E learning has emerged as one of the most used means of education where students of all ages will have an opportunity to learn flexibly, accessibly, and in a personalized way. The development of online platforms has accelerated, and now, with the help of these platforms, the learner can access thousands of courses, lectures, learning materials wherever they may be. Although this plethora of online information offers a wider choice, it also presents a major problem: learners tend to be unable to find the most appropriate tools, depending on their objectives, their capabilities and their learning styles. Consequently, information overload to many students results in a lack of motivation and

low performance in learning.

In a bid to resolve these challenges, E-learning Recommendation Systems (ERS) have become a necessity of the contemporary digital education. These systems interpret the learning behavior of the learner, the performance history, interests of the learner and the characteristics of the learning content and give individual recommendations. The recommendation systems assist the learners to select suitable courses, learning materials, videos, assessments, and learning courses that match their personal needs. ERS is able to boost learning through the provision of timely and appropriate recommendations thereby increasing the engagement of the learners.

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There have been a number of different forms of recommendation methods which have been proposed over the years such as content-based filtering, collaborative filtering, hybrid methods, semantic-based models and deep learning-based systems. All these methods have their benefits, but they also have certain issues like cold-start problems, sparsity of data, lack of understanding of context, and failure to represent complex learner behavior. As the artificial intelligence progresses, new opportunities to offer intelligent, adaptive, and context-based recommendations become possible.

This review paper gives an in-depth literature review of the current techniques of E-learning recommendations, its strengths, weakness and recent advances. The idea is to provide an in-depth picture of the existing research environment, outline the general obstacles to the creation of precise recommendation systems, and list the research opportunities that can be employed in the future to improve the personal learning experience.

I. BACKGROUND AND FUNDAMENTAL CONCEPTS

E-learning recommendation systems are designed to support learners in the process of making and recommending learning materials that apply to their needs, preferences, and objectives. To have a basic idea of how these systems operate, one should consider the basic concepts and technologies that underlie a current framework of the recommendation model.

A. E-Learning Environment

An E-learning is a digital setting, which includes LMS (Learning Management Systems), mobile learning applications, MOOCs, and virtual learning classrooms. These applications store different forms of learner data such as browsing, course interactions, assessment performance, time taken to access learning materials and user reactions. Recommendation systems use such data as their input.

B. System of Recommendation System

Overview.

A recommendation system is a smart program, which is created to process the information of users and suggest items that a user might enjoy. The courses, modules, videos, quizzes, learning paths, and assignments are some of the items that can be used in E-learning. The main objective is to make the learning personal through lessening of information congestion and enabling learners to

make sound choices.

C. Kinds of Recommendation Techniques.

i. Content-Based Filtering: Recommends learning materials that are like the ones that the user has already engaged with. It is dependent on metadata like topic, level of difficulty and learning style.

ii. Collaborative Filtering: Makes use of ratings and conduct of other learners of equal caliber to produce suggestions. It finds patterns among groups of users yet it is beset with sparsity of the data as well as cold-start issues.

iii. Hybrid Approaches: Integrate content-based with collaborative filtering to enhance coverage and accuracy. Hybrid models address numerous shortcomings of single models.

iv. Context-Aware Recommendation: Adds more context to the study, like when, what device was used, what the user was in a mood, what was his or her learning pace, or what was the learning objective to suggest something more meaningful.

V. Recommendation based on Deep Learning: Uses neural networks, embeddings, attention, and sequence learning to learn complex learner behavior and learning content relationships. Issues in E-Learning Recommendation.

This notwithstanding, E-learning recommendation systems have various challenges:

- Cold-start issue: New courses or users do not have enough data.
- The sparsity of the data: A significant percentage of learners do not review or rate courses on a regular basis.
- Dynamic preferences: The interests of the learners vary with time.
- Poor semantic interpretation: Systems have difficulties with understanding deeper meaning in material and learner behavior.
- Privacy issues: Sensitive data on learners will have to be secured.

This background determines the basic ideas that one needs to know in order to learn the techniques that one would see later in this paper.

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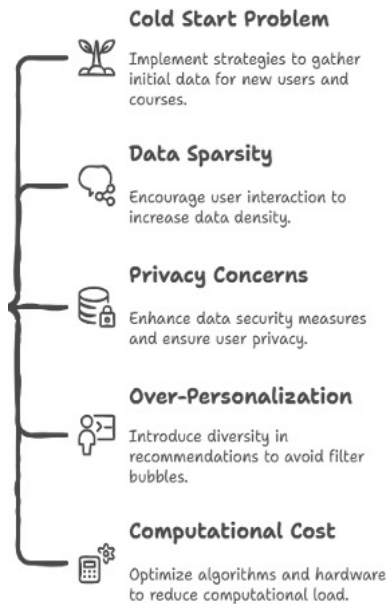


Fig. Limitations of different techniques used for Personalized E-learning Course Recommendation
Gathering data from different sources found to be more challenging task as the data is available with different sources. Density of the data should be more to access interactive application. As many portals or institutes are applied with high end security so collecting their data is critical task. Existing techniques recommendations are diverse with each student. Computational cost required to be less to provide user/student with quicker answer.

II. LITERATURE SURVEY

Bourkougou et al. (2016) suggested the individualized e-learning system based on the FelderSolomon psychological learning styles and the collaborative filtering to select the most appropriate learning resources. The authors emphasize that each student has his or her own learning style so that individual recommendations are necessary to enhance the learning outcomes. Their system creates a profile of the learner and constructs a dynamic learning scenario in accordance with the cognitive preferences of the student. This paper defines the way in which psychological modelling could greatly improve personalization in e-learning set ups.

El Youbi El Idrissi et al. (2023) dealt with the issue of information overload in e-learning platforms to design a personalized recommender system based on autoencoders. According to them, traditional collaborative filtering is afflicted by sparsity and dimensionality of data, which decreases accuracy. The system predicts the preferences of

learners much more accurately by extracting the features using autoencoders and learning the latent representation. Their deep learning-based model is demonstrated to be more effective than other types such as KNN, SVD, SVD++ and NMF in terms of RMSE and MAE, as compared to experimental comparisons show.

Amin et al. (2023) created both explicit and implicit-based learner feedback to facilitate a personalised course recommender model to IoT-driven smart education setting. The system combines machine learning algorithms which include: Random Forest, KNN, SVD, XGBoost, and Linear Regression in a collaborative filtering model to enhance prediction accuracy. Based on Coursera and Udemy datasets, the paper proves that SVD works better in terms of precision, recall, MAP, NDCG, MAE and RMSE. Their strategy demonstrates how smart learning platforms based on IoT could be used to facilitate adaptive and data-driven personalized learning.

An innovative multi-personalized recommender system called NPR_eL introduced by Benhamdi et al. (2017) integrates collaborative and content-based filtering to e-learning contexts. Conventional systems give all learners equal treatment, whereas NPR_eL changes the learning resources depending on the preferences, background knowledge, interests, and memory capacity. The authors combined this model to a real-world learning setting and showed that it is effective to provide more relevant and personal learning materials. They focus on the role of adaptation strategies in addressing the needs of different learners.

Madhavi et al. (2022) have offered an in-depth overview of e-learning systems and specifically concentrated on the concept of personalized recommendation techniques. The paper brings out the way e-learning environments need to be adjusted to meet the goals, talents, and interests of learners to increase the effectiveness of learning. Personalization has been attained using various techniques like clustering, classification, ontologies and association rules. It is also observed that the survey indicates the challenges in existing systems as well as mentions the growing significance of intelligent recommendation systems, particularly in the COVID-19 period when online education became a phenomenon. The authors arrive at the conclusion that the current e-learning recommender systems should be made more efficient and

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accurate when working with huge datasets of individual resources.

Bin et al. (2024) performed a systematic review of the existing personalized learning recommendation systems in the period between 2013 and 2023. This work is based on the analysis of 64 high-quality research articles found in the significant databases and the way learners and learning objects are modeled in the modern recommendation systems. It offers a comparison of the different algorithms applied in personalized learning such as collaborative filtering, content-based algorithm, and hybrid models. The unresolved issues identified by the authors include the ability to capture the behavior of learners and the large-scale problems, and suggest further research directions to enhance the personalized e-learning recommendations.

The Paper by Subha et al. (2023) presented a deep hybrid learning model to recommend online courses based on CNN, ResNet, and LSTM. Their framework combines the implementation of deep features and successive learning which helps comprehend the interests of the students and forecast the appropriate courses. The hybrid architecture enhances the accuracy of the recommendation through the strength of several deep learning models. The system can assist universities to suggest the next course to every learner and therefore make more informed decisions and enhance personalized learning paths in online systems.

III. COMPARATIVE ANALYSIS

The E-learning recommendation systems have developed in generations of algorithm, and every generation tries to enhance its personalization, accuracy and its interaction with the learner. A comparative study of available methods shows that there are differences in methodology, performance, and applicability in the various learning settings.

Content-based filtering methods are based on the analysis of course metadata, including the topics and levels of difficulty, to align the resources with the history of the interaction with a learner. Such models work well with systems whose user preference data is finite and well designed system with structured course descriptions. Nevertheless, they find it difficult to make various recommendations and tend to repeat the same, which limits the scope of exploration.

Collaborative filtering methods are based on the fact that the learners share similarities to come up

with recommendations. Such systems are usually very accurate when some historical interaction, rating and user behavior data are provided. They do well on large platform but fail in cold-start cases, where there are no interactions between the new users or courses. Also, there is still a significant issue of data sparseness since some learners are not habitual in giving explicit feedback.

The hybrid models are content-based and collaborative filtering in which they are more adaptable and precise with the recommendations. They are able to cover some of the weaknesses of individual methods, and they offer enhanced coverage and customization. Nevertheless, hybrid systems tend to demand more computation and more complicated combination of many data providers.

Semantic and ontology-based models integrate domain knowledge in order to provide recommendations of a semantically meaningful nature. These systems perceive ideas and connections among the learning resources leading to a high level of accuracy and a more appropriate recommendation. Although they are strong, ontology design and maintenance are tedious and may not be easily extended to other subjects and learning platforms.

The deep learning based recommenders have also shown a high enhancement in prediction accuracy, features extraction and learner behavior modeling. With neural networks, embeddings or attention mechanisms, such systems are able to learn more detailed patterns and are more responsive to changing preferences. They need however massive datasets, strong computing capabilities and hyperparameter optimization.

Comparing the various techniques, it would be evident that the conventional methods are simple and low-caliber, whereas the more advanced AI-based model is more customized and flexible. In general, hybrid and deep learning approaches provide the most promising results, and issues, including the sparsity of data, privacy, scalability, and interpretability, must be solved.

IV. RESEARCH GAPS AND CHALLENGES

Despite the fact that a lot has been achieved in the development of E-learning recommendation systems, a number of critical gaps and challenges have been left behind. Such constraints decrease the efficacy and precision of existing systems in addition to the necessity of new models. The cold-

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start problem is one of the biggest problems, in which the system is unable to produce correct recommendations to new learners or new courses to the system because there is no historical interaction data. On the same note, data sparsity is a common problem, as most learners fail to give ratings or feedback, which makes it hard to learn user preferences by algorithms, particularly the collaborative filtering models.

The other gap is the lack of capacity to know contexts of the learners. The majority of recommendation systems are based on the previous behavior only without any attention to such important factors as learning goals, time availability, emotional state, or preferred style of learning. Consequently, the suggestions might not necessarily be consistent with the actual needs and the conditions of the study of the learner.

The existing systems too have problems in semantic capture of learning materials. Most algorithms operate on content as plain text or metadata, disregarding more complex links among topics, skills and learning pathways. This diminishes the capacity of the system to give rich and meaningful recommendations that are conceptually rich. Large platforms that have thousands of learners and courses are still faced with the challenge of scalability. Deeper models such as deep learning demand and need a lot of computing capacity, huge datasets, and intricate optimization, which prevents most educational organizations, in its application.

The use of intelligent recommendation systems is also influenced by data privacy and security issues since it largely depends on personal data of learners. The ability to protect sensitive information and at the same time produce personalized suggestions is an open research problem. These predicaments demonstrate that as much as the existing systems are beneficial, more development is needed to come up with improved, adaptive and ethical E-learning recommendation systems.

CONCLUSION

E-learning recommendation systems have become an essential part of the contemporary online learning, helping a learner overcome the flood of information available online and choose the resources that respond to their interests and learning objectives. The paper has reviewed the available recommendation methods, such as content-based, collaborative, hybrid models, semantic and deep

learning methods. A comparative study revealed that unlike the traditional process, which is simple and efficient, sophisticated AI-driven models are more personal and flexible. Irrespective of these developments, there are a number of problems that still exist, including cold-start problems, data sparsity, insufficient contextual knowledge, scaling issues, and privacy issues. These limitations need to be dealt with in a smarter and context-sensitive manner that can be tailored to the needs of each learner. The review arrives at the conclusion that in future, the E-learning recommendation systems must concentrate on incorporating the recent technologies such as deep learning, reinforcement learning, GNNs, and privacy-preserving architectures to improve the overall learning experience. Overcoming the existing gaps and adopting the new trends, the E-learning platforms will be able to offer more precise, relevant, and personalized recommendations that will contribute to quality and interesting learning.

FUTURE SCOPE

The future trend of E-learning recommendation system is likely to be on enhancing personalization, flexibility and scaling. The application of deep learning and attention-based models can be considered as one of the promising directions since they could be used to observe the latent tendencies in learner behavior and make more precise recommendations. The other possible area is reinforcement learning, where the system has the capability of modifying the recommendations as time goes depending on the continuous learner feedback and performance.

Graph neural networks (GNNs) integration presents a chance to represent the association between students and courses as well as courses and subjects and skills in a manner that allows to make more meaningful and structured recommendations. By adding emotion-sensitive and behavior-sensitive learning analytics to the system, it may be possible to encourage the systems to become aware of the level of motivation, fatigue, and involvement of learners, resulting in more context-informed recommendations.

Multilingual and multicultural recommendation systems are also of interest in the growing interest as they can offer services to different learners in various areas. Furthermore, federated learning and privacy-sensitive models will also become necessary in order to make sure of the protection of the learner data and ethical use of

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the data with preserving the personalization. Real-time recommendation engines can also be incorporated in mobile learning platforms in order to guide the learners in real-time. All in all, the future of the E-learning recommendation systems is on intelligent, adaptive, secure, and user-centered models that continually learn with the behaviors of the learners and provide high-quality learning paths to them.

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