JOURNAL OF BASIC SCIENCE AND ENGINEERING

LEVERAGING MACHINE LEARNING-DRIVEN RECOMMENDER SYSTEMS FOR ENHANCED STUDENT ENGAGEMENT AND MOTIVATION

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DOI: https://doie.org/10.10399/JBSE.2025420040

Abstract: To improve student engagement, retention, and learning results, this study focuses on incorporating customized learning systems into massive open online courses (MOOCs) using RS based on machine learning. There are two issues that massive open online courses (MOOCs) confront, and customized learning systems address them. These challenges are high dropout rates and insufficient individualized assistance. Adapting learning routes based on individual learner profiles may be accomplished by utilizing various recommendation systems, such as collaborative Filtering, reinforcement learning, and hybrid models, as demonstrated by research. As a result, these methods guarantee that students are eager to learn and actively involved in the process, both of which are essential to successful online learning. The study demonstrates how tailored suggestions will respond to changes in the demands of learners by using data such as clickstream and learning behavior. This will result in improved academic achievement and increased levels of pleasure. On the other hand, based on some ethical considerations, particularly about fairness, transparency, and bias in the recommendation algorithm, it is a major concern that these systems exploit learner data. At the same time, there is always a probability of reinforcing bias concerning certain demographics, prior knowledge, or socioeconomic background. Based on the study's findings, a greater focus should be placed on fairness-aware models, in which all students are given equal opportunities to learn, regardless of the situation in which they are learning. This may be accomplished only via the development of bias-reducing algorithms so that learners can take full responsibility for making decisions regarding their educational pursuits. Personalized learning systems hold significant promise to change massive open online courses (MOOCs) by boosting student engagement and retention and improving learning results. This is the other inference that can be drawn from this study. However, for them to be applicable on a big scale, they need to be created with strong ethical considerations to prevent any group of students from being disadvantaged and to guarantee no data privacy breach. Future research has to be planned to improve scalability, fairness, and high ethical standards when establishing individualized models for learning; this will better equip online platforms to be accessible, inclusive, and successful across a global platform.

Keywords: Personalized learning, Massive Open Online Courses (MOOCs), recommender systems, machine learning**,** E-learning, Student engagement and motivation.

1 Introduction

Personalized learning is an educational strategy that focuses on adjusting training to each student's particular requirements, interests, and skills. Since students have different learning styles, approaches, and objectives, this approach aims to provide them with a customized learning experience that meets their specific requirements. Online learning platforms and conventional classrooms are only two educational contexts in which personalized learning may be used. Giving them a more tailored and relevant learning experience may raise student motivation, engagement, and learning results. But to succeed, it needs thorough preparation, continual evaluation, and expert facilitation. Adaptive learning is said to be the teaching methodology to make learning experience of each students to be distinctive. For analysing learning style, and total performance of students, machine learning and data analytics approaches can be used. The substance of the course material and the difficulty level are then adjusted to cater to each student's specific needs within the context of the online learning platform.

The fast growth of network information technologies has resulted in massive open online courses (MOOCs) being one of the most successful online learning platforms. Learners are finding it increasingly challenging to select the courses they wish to take due to the growth of online courses. Due to this, kids do less well when they are learning. Considering that Recommender Systems (RSs)[1], [2] are talented with handling the information overload issues, [3], [4], and course suggestions which are customized [5],[6],[7] have been the main field of study to address the issues above in recent years. A wide range of courses are available on MOOC sites. Developing the skills necessary for the learner's desired future employment is crucial to advising them on the best route. For example, a student's level of proficiency in a certain subject might be determined by their learning accomplishment in the course. The skills, knowledge, and competencies that online courses provide may be compared to those the workforce needs to achieve the course's learning goals. In addition, sequential RSs [8] use a series of previous interactions to determine the learner's future interests and recommend the next item or learning material. On the other hand, interactive recommendation systems can generate suggestions based on input from learners via ongoing interactions. However, as educational institutions increasingly prioritize individualized and flexible learning, the use of AI in administering online learning will proliferate. Students from around the globe may enrol in any program (course) using AI-powered technology.

A few approaches evaluate the Recommender Systems(RS's) flexibility while analyzing students' e-learning learning activities [9]. For example, [10]developed a technique for MOOC called adaptive recommendation. Grades are used by adaptive RS and study the schedules as standards for suggestion. The learning action has not yet developed and so the item must deal with specific requirements is recommended. One learner who shares this viewpoint supports the suggestion of collaborative-based Filtering. The time series from the adaptive viewpoint is used in the second. Using comparable learners' grades and study schedules to integrate Just as much creativity is required for the time series of learning activities geared toward the target student. Due to the development of information technology, massive open online courses (MOOCs) have become significant venues for expanding knowledge. Learners are now having a more difficult time picking acceptable learning materials from a wide range of academic resources owing to the rising volume of accessible data. This is particularly true even though the problem involves several factors. One approach that may be taken to address this problem is to use a Personal Recommender System (PRS) based on RL.

By offering engaging material that aligns with users' interests, Personalized Recommender System(PRS)[11], [12] may lessen the problem of information overload. Recommendation algorithms often employ a range of data to show people possible items. Based on past user-item interactions, the RS suggests items in real-world situations and then gathers user feedback to improve those suggestions [13]. In other words, the RS uses user interactions to learn about users' preferences and recommend things they may find appealing. The first recommendation research primarily focuses on developing content-based and collaborative-based filtering strategies to accomplish this [14],[15]. Collaborative-based filtering techniques [10], have been used by conventional recommendation systems [16] [17] [18], to collects implicit comments which slightly explored the preferences of learners. Neural recommendation systems based on deep learning have recently outperformed these techniques [16], [19]. The neural attentive session-based RS [20]is one such model that mimics users' sequential behaviours and infers users' main objectives from their learning patterns. Furthermore, noisy courses are decreased by the basic RS based on the attention network and the profile reviser concurrently produced by the hierarchical Reinforcement Learning technique [21]. On the other hand, the performance of course recommendations may be improved when students are enrolled in many courses. Hierarchical Reinforcement Learning(RL) may provide subpar recommendation results as it ignores the student's clear requests and implicit preferences.

Many colleges and universities are acknowledging this concept and methodology. The MOOC system facilitates online learning and Information sharing by offering free courses and creating an online learning environment. Now that so many network resources are available, students find it challenging to quickly and accurately find the appropriate course materials[15][22]. Hence, the current study goals in curriculum recommendations are to better disseminate knowledge, communicate pertinent Information to those in need, reduce duplicate knowledge development, and promote a more extensive audience's more efficient use of knowledge.

The Internet and big data analysis technologies provide learners with substantial advantages, and including MOOC resources in the learning process is essential. However, the diversity and accessibility of platforms like Udacity, Coursera, Udemy, and edX have made it challenging to locate appropriate MOOCs, and students may get overwhelmed by the abundance of available knowledge[23][24]. With the increasing demand for distance learning, RS solutions have surfaced to enhance the quality of course choices and assist students with the deluge of accessible course material[25]. RS, a MOOC-based platform, suggests high-quality courses to students. Personalized EL and MOOC RS are examples of how IoT may enhance education. These tools may gather Information on students' learning preferences, passions, and development to provide the most interesting and relevant material. As a result, students may learn more quickly and effectively. Personalized EL and MOOC RS are valuable resources for enhancing intelligent learning. Students may study more swiftly and successfully with the support of these platforms, which provide the most interesting and relevant material.

Our study is to develop a Personalized Course Recommender (PCR) system that uses Machine Learning (ML) and Collaborative Filtering (CF) techniques for predicting students' academic performance and recommending suitable courses. The study compares the effectiveness of CF and ML techniques while addressing ethical considerations to ensure unbiased recommendations. Course content will be classified according to beginner, intermediate, expert levels and difficulty, and also recommended on explicit (from users' ratings) and implicit learner feedback, such as lectures viewed, assignments done and article interactions.

The study also incorporates personalization features, considering learners' preferences, past performance, contextual knowledge, and IoT-enabled device usage patterns. The proposed PCR aims to deliver top-ranked personalized course recommendations by designing and assessing an innovative educational framework, enhancing engagement and optimizing the brilliant e-learning experience.

As a result, it is of the utmost importance to carry out a thorough and methodical analysis of the existing literature concerning individualized and adaptive learning techniques that use machine learning algorithms such as content-based Filtering, collaborative Filtering, and hybrid recommendation models[26]. This is part of examining their effectiveness in customizing course suggestions according to learner profiles, interests, and behavioural patterns. As a result, this study's primary research question has been developed as follows:

"*What are the advancements in machine learning-driven recommender systems for adaptive and personalized MOOC learning, and how have these methods enhanced student engagement and motivation in online education environments?"*

The following sub-research questions are developed to find the answer to the primary research question of enhancing personalized course recommendations in MOOCs through Machine Learning and Collaborative Filtering techniques:

- How can Machine Learning and Collaborative Filtering Techniques be integrated to enhance the accuracy and relevance of course recommendations in MOOCs?
- How do personalized course recommendations impact student engagement and motivation in an online learning environment?
- How can personalization approaches in MOOCs and e-learning enhance learner engagement, retention, and achievement of learning outcomes?
- What are the ethical considerations and challenges in ensuring fairness and bias-free recommendations in personalized learning systems for MOOCs?
- How can personalized course recommender systems be scaled and implemented across multiple MOOC platforms to improve global learning experiences?

This project develops and applies customized and adaptive learning methods for Massive Open Online Courses. From early approaches to the newest advances in machine learning (ML) and collaborative Filtering (CF), the study examines course recommendation systems. It shows how they solve particular issues in online learning. The research shows how these strategies are used across domains to address learner engagement, course relevance, motivation, and their practical consequences. The paper examines the pros and cons of different techniques by analyzing recommender systems' complexity, such as their capacity to handle diverse learner data, adapt to different learning behaviours, and scale. This review provides detailed advice to help new and seasoned researchers create novel customized learning system solutions. The long-term objective is to advance the field and promote innovative solutions to adaptive learning challenges. This study's primary contributions:

- ➢ To assess the impact of personalized recommender systems on learner engagement and retention in MOOCs.
- ➢ To identify the key challenges in developing and implementing recommender systems for MOOCs and suggest strategies to address them.
- ➢ To design and evaluate the effectiveness of machine learning and collaborative filtering techniques for improving course recommendations in MOOCs.
- ➢ To compare various recommender system algorithms based on accuracy, scalability, and learner satisfaction.
- ➢ To explore potential advancements and future directions in personalized learning systems within MOOCs.
- ➢ To analyze the influence of different types of learner data on the performance of recommender systems in MOOCs.
- ➢ To examine how adaptive learning systems can be integrated with recommender systems to improve the learning experience in MOOCs.

Vol. 22, No. 1, (2025)
ISSN: 1005-0930

This study is well-structured and divided into different sections to achieve a comprehensive view of personalized course recommender systems in MOOCs. The research methodology with research objectives, data collection, selection criteria, and inclusion-exclusion guidelines can be found in **Section 2**. **Section 3** discusses how machine learning techniques can be merged with collaborative Filtering to improve the course recommendation services offered by the MOOC. **Section 4** investigates the impact of personalized course recommendations on student engagement and motivation in online learning environments. **Section 5** focuses on personalization approaches in E-learning and MOOCs. **Section 5.1** examines the core parameters of personalization, and **Section 5.2** presents proposed solutions for optimizing personalization strategies, including the design and implementation of MOOCs' personalization systems. **Section 6** focuses on ethics and challenges in ensuring fairness and reducing bias for personalized learning recommendations. **Section 7** focuses on the scalability and realization of personalized course recommender systems on various MOOC platforms. Therefore, through this structured presentation, the goal is to see how such improvements in global learning experiences can be made via these systems in MOOCs.

2 Methodology

This section details the methodical approach taken to locate, assess, and assess literature on various topics related to educational technology, including personalized learning systems, recommendation systems (RS), scalability issues, fairness concerns with Massive Open Online Courses (MOOCs), and ethical considerations. We cared to screen thoroughly and eliminate prejudice using an organized and methodical methodology. Search tactics, keywords, databases, inclusion and exclusion criteria, and a comprehensive methodology are all laid forth here.

2.1 Keywords

Several targeted keywords were developed to ensure the retrieval of relevant literature based on the main objectives of this study. A broad set of keywords was initially created and then reduced and refined to focus on the specificity of the study. These included various terms that reflected aspects related to personalized learning systems in MOOCs, recommendation systems, scalability challenges, fairness, and ethical concerns in educational technology. The final list of keywords was "personalized learning systems," "recommendation systems (RS) in education," "reinforcement learning in MOOCs," "scalability of personalized learning," "fairness in educational technology," "bias in recommendation algorithms," "ethical concerns in personalized learning," "adaptive learning systems," "learning path personalization," "hybrid recommendation systems in MOOCs," and "bias mitigation in educational systems." Keywords were also combined to find more specific aspects of the literature, such as "reinforcement learning and scalability in MOOCs" or "ethical issues in personalized learning algorithms." All of this was to ensure a proper literature search that considers every aspect of the focus of the study.

2.2 Academic Databases

The literature search was conducted using several reputable, peer-reviewed academic databases to ensure a wide-ranging selection of high-quality sources. The following databases were consulted to collect the relevant publications:

- Google Scholar
- IEEE Xplore
- SpringerLink

- ACM Digital Library
- Taylor & Francis Online
- Elsevier ScienceDirect
- Wiley Online Library
- JSTOR

These databases offer access to various academic journals, conference proceedings, and edited volumes, so the literature set is comprehensive. A time range from 2009 to 2023 was used to limit the scope of the most current developments in personalized learning systems and recommendation algorithms within MOOCs. This enables us to view the latest developments while considering foundational studies that have moulded the field.

2.3 Article Inclusion/Exclusion Criteria

To ensure that only relevant articles were included in this review, we established clear inclusion and exclusion criteria. The articles were initially screened based on their titles and abstracts, followed by a full-text review to determine their relevance to the study. The inclusion and exclusion criteria are summarized in Table 1.

Table 1 Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
✓ Articles that focus on personalized learning systems and recommendation algorithms in MOOCs.	✓ Articles that discuss broad educational technologies without focusing on recommendation systems.
✓ Research on the application and development of recommendation algorithms in MOOCs.	✓ Articles that review only specific performance metrics or evaluations in one domain.
✓ Studies addressing scalability and fairness challenges in personalized learning and recommendation systems.	✓ Papers that do not focus on ethical issues or fairness in personalized learning systems.
✓ Articles explore integrating reinforcement learning, machine learning, or hybrid systems in MOOCs.	✓ Studies outside the scope of MOOCs or personalized learning systems.
✓ Only English-language publications were included.	✓ Non-peer-reviewed sources such as blog posts, white papers, or conference slides were excluded.
✓ Peer-reviewed journal articles, conference papers, and edited book chapters were considered.	✓ Articles published in languages other than English were not considered.

2.4 Article Selection Process

Initial Screening: The abstracts, titles, and keywords of the articles were reviewed to gather Information on the articles that are directly relevant to the study's objectives. Articles not related to personalized learning in MOOCs, recommendation systems, or scalability challenges were excluded.

Full-Text Review: After the preliminary screening, the full text of each article was read to evaluate its relevance and methodological quality. Only studies that directly addressed the integration of recommendation systems in MOOCs or explored scalability and ethical concerns were included.

Data Extraction: Information extracted from each paper included

- The type of recommendation system used (e.g., collaborative filtering, content-based, hybrid models).
- The challenges are addressed, particularly in terms of scalability and fairness.
- Any ethical issues, such as bias in recommendation algorithms or student autonomy.
- The impact of personalized learning systems on student outcomes.
- Future research directions proposed in the studies.

3 Integrating Machine Learning and Collaborative Filtering for Enhanced Course Recommendations in MOOCs

Nowadays, many educational institutions are using the benefits of the internet, AI, and big data analytic technologies to promote intelligent education by the indicators set out by the Ministry of Education. Massive open online course (MOOC) materials are the backbone of smart education initiatives [27],[28],[29]. Consequently, there is a great deal of academic interest in developing a collaborative filtering recommendation algorithm for massive open online course (MOOC) materials[30],[31]. Massive open online course (MOOC) resource recommendation algorithms have arisen due to the ongoing advancements in big data technology. Numerous top-notch MOOC resource suggestion algorithms have been developed with recommendation technologies in online commerce, tourist routes, and social networks [32],[33]. A massive open online course (MOOC) has the potential to accommodate over 100,000 students, whereas a traditional classroom may only have dozens or hundreds[34]. Consequently, art-learning MOOC materials are recommended online via collaborative Filtering [35],[36]. The current collaborative filtering recommendation system for art learning is struggling to keep up with the ever-increasing number of resource data. The MAE values are larger since MOOC resources can only be surface-level. Automatic extraction of deep features is a capability of deep learning. “Collaborative filtering recommendation algorithm for MOOC resources based on deep learning” is therefore proposed in this paper as a solution to the existing issues with this procedure.

The **figure1** shows how a recommendation system[37], which is prevalent in massive open online course (MOOC) systems, works[38]. Choosing a course or subject area of interest is the first step. After this data is entered, the algorithm starts to provide suggestions. To improve future suggestions, the system updates the user profile based on the input the user gives on these suggestions. With each iteration, the algorithm becomes more thoughtful about the user's tastes and can tailor its suggestions to them more and more. Two important recommendation methods, content-based Filtering and collaborative Filtering, are also shown in the figure 2. Content-Based Filtering suggests products comparable to those the consumer has already engaged with. By contrast, Collaborative Filtering suggests products according to the tastes of other users who are similar to the individual in question. A more interesting and fruitful learning experience for MOOC users may be achieved by incorporating Machine Learning methods into these approaches, which can further improve the accuracy and customization of recommendations.

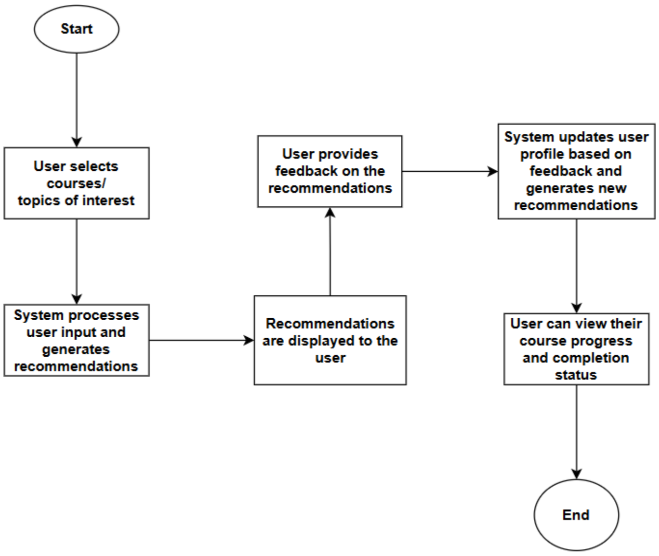

Figure 1 Flowchart of Course Recommendation System

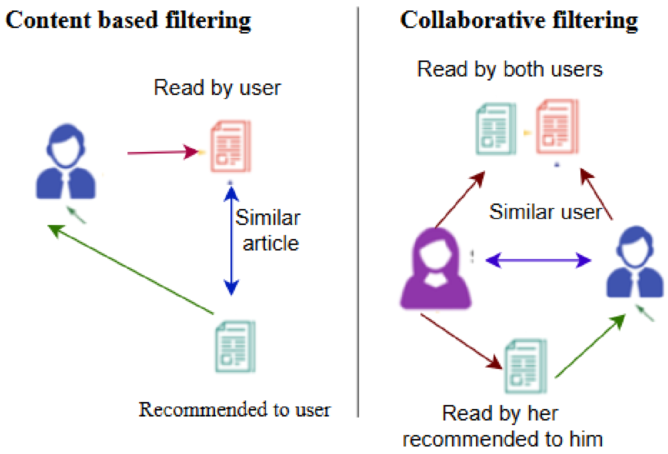

Figure 2 Comparison of Content-Based Filtering and Collaborative Filtering [39]

4 Impact of Personalized Course Recommendations on Student Engagement and Motivation in Online Learning Environments

Low academic performance, social isolation, and high dropout rates are all issues that may be addressed by student engagement, according to a previous study [37]. In an online setting, where students could feel lonely and detached, student engagement is crucial to their learning [40]. When students actively participate in a class, they pay attention to the course content, their peers, and the teacher. According to many studies [41][42], [41], [43], actively involving students is crucial for maintaining their interest in the course and, therefore, their learning. Researchers looked at online learning platforms and more conventional classrooms to see how engaged students were. An example would be examining the correlation between student data and involvement using a range of input attributes and approaches [44]. [45]monitored students' engagement as they saw films. Student engagement with the video and the frequency of their evaluations served as the study's input variables. According to research by [45], students' performance improves when they use course resources; students generally anticipate that learning course content would result in higher scores. Test results are significantly affected by students' engagement in interactive learning activities, according to [46]. Prior studies have shown a favourable correlation between student engagement and course ratings. For example, it details how students routinely pass tests and obtain course materials online to get better grades. Research by [47] and others has shown that students who actively participate in class and fill out surveys have better overall academic outcomes.

According to [40], online learning engagement was influenced by skills, emotion, involvement, and performance. Skills are a category of learning that includes activities such as taking notes, practising every day, and paying attention while reading and listening. A learner's feelings regarding learning, such as their desire to learn, are their emotions. "participation" describes how a student behaves during class discussions, chats, or conversations. Performance is an outcome, like a high-test score or grade. Usually, the engagement mentions about the students who invested in efforts, skills and time to associate positively with other students in classroom and also engages in emotional learning in certain capacity (i.e., be inspired by a concept, want to learn and interact). Personal attitudes, beliefs, actions, and interpersonal communication contribute to student involvement. Thoughts, work, and emotions are present somewhat during learning. Therefore, as seen in Fig. 3, scale of student engagement focuses on quantify what the students are undertaking and how they associate with their learning and how they associate to faculty, students, resources in between other things like abilities, engagement/communication, performance, and feelings. Therefore, earlier studies have looked at techniques to enhance online learning rather than just comparing online and in-person classrooms[48],[49],[50]. Previous studies reviews on student engagement exhibits that activities participation, learning efforts, learning satisfaction and interaction are significant student engagement indicators in learning environments [51],[42],[43]. These findings highlight several characteristics of online learning environments that might serve as gauges of student engagement. Online learners who are successful and engaged utilize online technology well, have the psychological motivation to learn, and make appropriate use of their past experiences. They are also skilled at both cooperative and self-directed learning, and they have outstanding communication skills [52],[53].

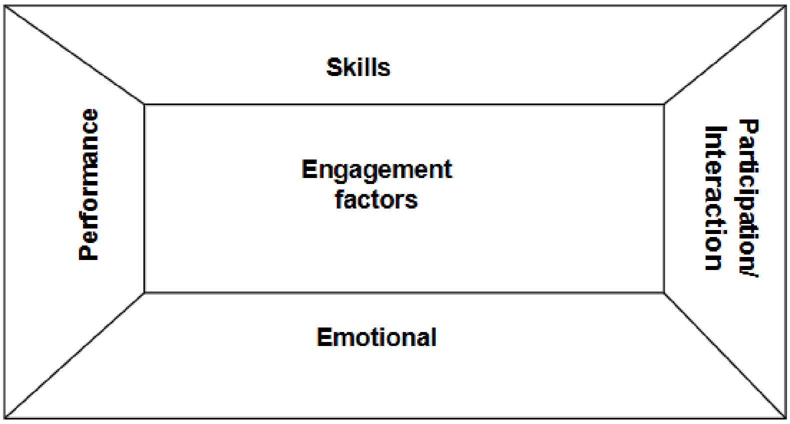

Figure 3 Student Engagement Framework in Online Learning

5 MOOCs and E-learning- Personalized strategies

Global personalization of MOOCs refers to altering a system's behaviour and features to suit the user's needs. A particular user's profile determines the customization that is suggested for them. A user's profile is an instantiation of the user model that includes details about the individual. A well-established and growingly significant research area is personalization in MOOCs. To illustrate customization in the educational context, several definitions and justifications have been put forward. According to [54], customization organizes learning pathways to accommodate each learner's demands. Individual learning is defined by [55]as modifying pedagogy, curriculum, and learning environments to accommodate each learner's unique learning requirements and preferences. Personalizing learning environments aims to shift the conventional viewpoint of teacher-centred instruction toward a learner-centred one. According to [56], 3 concepts can be personalized in learning settings and they are, i) the Information that students get during the learning process, (ii) how and when the Information is provided, and (iii) how students are assessed.

5.1 MOOCs and E-learning- Personalized strategies

The previous authors shows many strategies for MOOC and E-learning personalization ($Essalmi, Ayed, Jemni, Graf, et\ al., 2015$). The following table 2 shows personalized strategies examples in MOOCs and E-learning.

Table 2 Examples of personalization approaches for E-learning and MOOCs

Authors	MOOCs/E-learning	Narrative
[57]	E-learning personalization: A novel method based on two layers for customizing e-learning scenarios	The method offers metrics for evaluating e-learning customization tactics according to their viability and effectiveness when used with a wide range of learning materials and learner attributes.
[58]	MOOCs personalization: Competency-based personalization for massive online learning	The MOOCs were personalized with several restrictions according to the parameters to consider when recommending material. We provide the following as examples: resources that consider the learner's degree of expertise.
[59]	Personalization of E-learning: Generalized metrics for the e-learning personalization strategies analysis.	The developed clarification is a stage towards merging the study determinations on E-learning personalization through combining and incorporating the parameters of personalization.
[60]	MOOC personalization: Adaptive planner for facilitating the management of MOOCs tasks.	An application is designed to direct the learners who lacking in learning and skills based habits in reading most of the MOOC contents. The efforts shows the main component of application which is said to be the adaptive planner.
[61]	MOOC personalization: Adaptive recommendation system for MOOC	Based on the criteria which is to be considered in suggestions of contents and different limits have explained in MOOCs personalization. The resources

		are considered based on learner's preferences.
[62]	MOOC personalization: Towards an MOOCs filtering and outcome-based discovery using MOOC rank.	It supports the users in identify the highly suitable elements for him from specific set of MOOCs information.
[63]	Personalization of MOOCs: Pedagogy mechanism case study and scalable cloud mechanism.	The type of customization implemented in MOOC adaptation
[64]	MOOCs Personalization: Critical Literature Review	The significance in offering social platforms for the learners in strengthening their connections with course contents.

Other methods provide learners suggestions in MOOCs. Example: [62]proposes a strategy to assist learners in meeting MOOC learning goals. The learner model includes MOOCs previously practised by the student. To get this Information, ask the learner directly. Assessments from the present MOOC and similarity calculations with other MOOCs determine this. According to [65], a conversational agent is suggested to promote MOOCs. The approaches or strategies for customization are identified in enhancing online learning and MOOCs retention rates. These researches struggles in improvising the open education quality, in this study, we evaluate the learners who are not successful MOOCs and develops a way in enhancing the retention rates.

5.1.1 Parameters of personalization

Our goal is to tailor MOOCs to motivate and focus students. Numerous customization systems exist with diverse settings ($Chorfi$ & $Jemni$, 2004; $Essalmi\ et\ al.$, 2007, 2010, 2015).
All strive to create customized courses based on learners' attributes. Table 3 shows set of personalized parameters and their strongest values explained in researches and used by the teachers in personalize the courses.

Table 3 Personalized Parameters values examples

Personalization factors	Set of values
Learner's level of knowledge	{beginner, intermediate, advanced} [66]
Learner personality	{Introvert, Extrovert, sensing, intuitive} [67]
Kolb learning cycle	{Converger, Diverger, Assimilator, Accommodator}[68]
$Honey\text{–}\ Mumford\ learning\ style$	{activist, reflector, theorist, pragmatist} [69]
$Felder\text{–}\ Silverman\ learning\ style$	$\{sensing, intuiting\}$ $\{visual, verbal\}${active, $reflective\}$ $\{sequential, global\}$ [70]
$La\ Garanderie\ learning\ style$	{competitive, cooperative, access on the avoidance, participative, dependant, independent}[71]
Motivation level	{low, moderate, high} [68]
Navigation Preference	{breadth-first, depth-first} [72]
Cognitive traits	$\{low\ working\ memory\ capacity, high\ working\ memory\ capacity\}$ $\{low\ inductive\ reasoning\ ability, high\ inductive\ reasoning\ ability\}$ {low information processing speed, high information

	processing speed} {Low associative learning skills, high associative learning skills.} [73]
Pedagogical approach	{objectivist, competencies-based, collaborative} [74]

5.2 Personalization strategy optimization using proposed solutions

The following section presented the framework for personalized strategy selection optimization in MOOCs. It also shows clustering algorithm.

5.2.1 Personalization system- MOOCs

The architecture for our MOOC customization strategy is analyzed in this section. The system's user interface for teacher communication is displayed in Figure 1. The Database contains learner interaction traces needed to evolve profiles. The K-Means algorithm identifies learners and creates individualized tactics. The algorithm offers new tasks and pathways for each student based on their educational game interaction traces, and this cycle continues as fresh data is created.

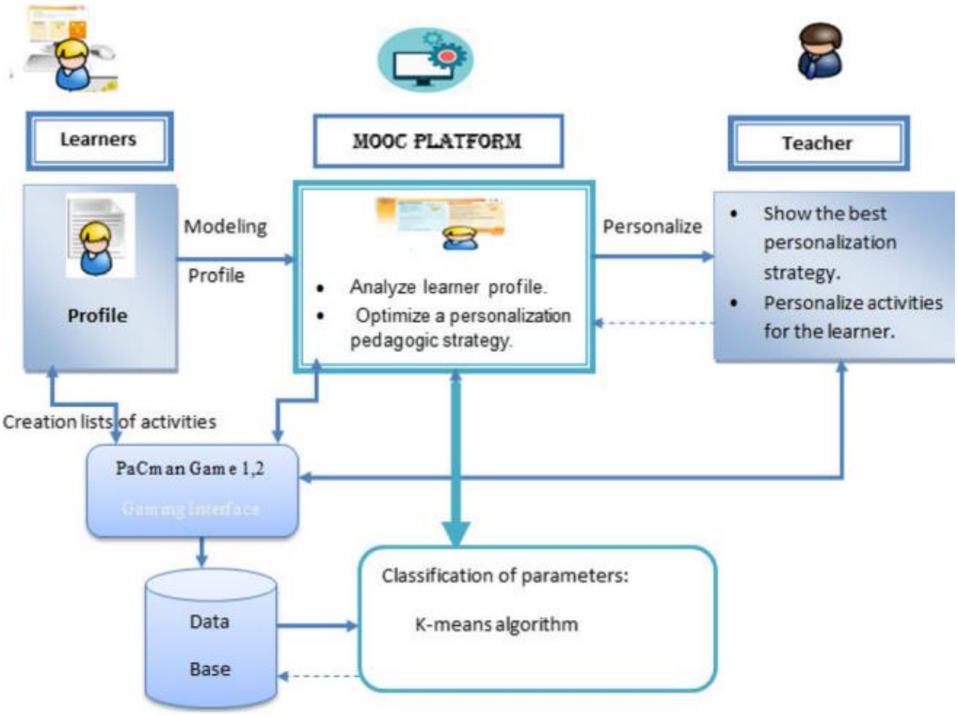

Figure 4Proposed architecture of the MOOCs personalization strategy [75]

6 Ethical Considerations and Challenges in Ensuring Fairness and Bias-Free Recommendations in Personalized Learning Systems for MOOCs

In the world of education, there has long been worry over student retention in MOOCs (Massive Open Online Courses). Numerous factors, such as a lack of time, insufficient support, and difficulties with motivation, have been linked in studies to student dropout[76]. In light of the high dropout and failure rates seen in early research on remote and online education, MOOC personalization aims to solve these problems[77],[59] [8, 9]. According to research, MOOC participants often need individualized assistance, such as tailored follow-ups, to remain motivated and involved. A significant percentage of students drop out of the course without such individualized procedures, underscoring the need to use customization to solve the problem of student retention.

Although MOOCs have the potential to expand learning possibilities [78], there are drawbacks to this scalability, especially when it comes to guaranteeing worthwhile learning experiences. Successful learning outcomes depend on students actively engaging with the course material, classmates, and teachers [79],[80]. However, given the size of MOOCs, it may be challenging to create instructional strategies that accommodate a variety of learners while retaining active participation [81],[82],[83]. This problem is said to be solved by customized learning, although successful large-scale implementation of personalized systems is still a work in progress [[84]; [85]].

To customize the learning process at scale, several research have looked at integrating recommendation systems into MOOCs [86],[87],[6]. These technologies provide tailored learning routes or match a learner's profile to the suggested material [[88]; [89]. However, as [84] pointed out, MOOCs shouldn't impose a one-size-fits-all strategy on more complex subjects. Instead, the freedom to choose their learning routes within the course should be granted to the students. To provide real-time adaptive learning experiences, [90], for example, customized learning routes by examining learners' clickstream data (such as time spent on sites). [91] also addressed the issue of scaling customization by modifying assessment questions according to learners' prior interactions, including quality and complexity. Their results show that scalable, customized learning is achievable with enough datasets and expert evaluations.

Ethical concerns about prejudice and fairness in recommendation systems are critical, even when these tactics seek to improve individualized learning. To guarantee that every student, regardless of background, has an equal chance of success, personalized learning methods must be planned appropriately. Some students may have an unfair educational experience due to the possibility of reinforcing prejudices, whether based on socioeconomic background, past knowledge, or demographic characteristics. Transparency in the data used to customize learning routes and algorithms that do not unduly favour certain groups over others is necessary to ensure fairness in MOOCs. Additionally, to keep the system from becoming too rigid or one-dimensional, customization must be balanced with concerns about student autonomy and a variety of learning requirements. A persistent problem for academics and educators is the continual development of ethical standards and strategies for mitigating bias in MOOCs.

7 Scaling and Implementing Personalized Course Recommender Systems Across Multiple MOOC Platforms for Global Learning

Researchers have made substantial contributions to understanding RSS and have offered practical solutions for item recommendation via supervised learning and reinforcement learning techniques. According to the RL technique[92], [93]concentrated on developing an RS that can determine each student's ideal quantity and timing of tests. An RL-based online recommendation method was created by [94]. The authors made an RL agent that operates constantly and dynamically in action space, depends on $state - action - reward - state - action\ model$. Better action course decided the agent and the model’s performance is analysed by actual dataset from an OL system.

Vol. 22, No. 1, (2025)
ISSN: 1005-0930

Nevertheless, since the square root of the mean squared error is significant, the forecasts' accuracy still has to be improved. Investigating the different RL techniques is crucial in addition to the strategy for figuring out the optimal values of the $greedy$, $learning\ rate$, and $discount\ rate$. Similarly, [95]used machine learning and knowledge discovery approaches to offer an agent-based recommendation for e-learning. In another similar study, [96]used a DRL based method for suggesting news whereas $Esfahaani\ et\ al.$ suggested RS for advertising online using DRL. Other studies on movie suggestions have been conducted using RL techniques[97],[98]. They developed an RL-based single agent to provide recommendations; however, if different patterns are seen for various user groups, the models cannot adequately adjust for numerous users because they encounter fundamental issues while attempting to deploy a single agent to perform many activities, including feature space. An alternative strategy for enhancing learning performance is using numerous agents to carry out comparable tasks simultaneously. Therefore, the current research must be expanded to improve the accuracy of the suggestions.

For personalized course recommendations, [99] established hierarchical RL using dynamic recurrent framework. For abalncing exploitation and exploration, policy gradient method has used in user profiles. For study the future preference of users, dynamic baseline has used and for analyse the current knowledge context aware learning technique has used. Moreover [100] recommended sentiment analysis based on hybrid $Elman\ similarity - based\ e - learning\ course\ RS\ framework$. Similarity measurements used by sentiment classification model. MOOC recommendations for RS single course developed by [101] using multi-granularity sessions and multi-type interests. User-interactive activities with factorization of tensors, network structured features and graph neural networks combined and [102] generated hybrid RS. Graph based teaching evaluation network has developed using the student feedback, personal relationships, ratings and grades, used for explaining courses, entities and students. After every student obtained their patterns of relationships, neural network using random walk method is vectorized them. $Bayesian\ probabilistic - based\ tensor\ factorization$ predicts and learns pre-attendee ratings of lecture. The third dimension of tensor ratings is built by the customization characteristics.

Furthermore, for MOOC environment, [103] recommended edX, Khan Academy and Udemy course portions in RS. Student profiles used by this methodology for developing the interactions and natural environment. 19 students were investigated from 3 MOOC sites explained that the selected processes are highly believable. Also their recommendations are $62.24\%\ right$, $68.89\%\ value$, $72.81\%\ reliable$, and $99.12\%\ new$. It helps students to address the knowledge gaps expressed from outcomes. Also, [104] established RS to encourage MOOC courses based on student behaviour and preferences using ML. from online learner reviews multi-criteria analysis are used for establish the technique. $Latent\ Dirichlet\ Allocation$ for decision tree, text mining, self-organization maps for learner courses fuzzy rules and evaluations for prediction of preferences. They also implemented for feature selection method to select the most significant features for learner preferences prediction. Udemy information has used for strategy analysis. The information showed that the method rightly suitable for learner desires with appropriate courses.

[5] proposed $xSVD++RS\ model.$ here x shows the $multi - dimensional\ matrix\ factorization$ structure and the $CF\ technique$, which forecasts course trends and makes rating predictions using external data like users' abilities and course attributes. [105]examined RS in MOOCs beyond prediction accuracy. To improve RS adaptability, [106] recommended dynamic framework and hierarchical RL course. And [107]

established $Top - N\ customized\ RS\ in\ MOOC$ using $graph\ neural\ network$ to flexible with learners and for course suggestions attention method is used. [108] proposed recurrent context-aware and hierarchical RL. User profiles were rebuilt for course recommendations. [109] uses RS for guides students for suitable courses. The approach uses social filtering and sentiment analysis for identify the better way for students to learning and recommending courses which is suitable for the social media and profile content.

8 Conclusion

The study's findings demonstrate the enormous potential of recommender systems powered by machine learning to revolutionize MOOCs' educational process. Improved student motivation and engagement may result from customized course suggestions that are adapted to each learner's requirements via the integration of cutting-edge strategies like collaborative Filtering, reinforcement learning, and hybrid recommendation models. According to the study, these technologies are excellent in creating a more personalized and flexible learning environment, which eventually enhances learning outcomes, retention, and general student satisfaction in online learning.

But the research also recognizes the difficulties in putting customized learning systems into practice, especially when it comes to fairness, transparency, and bias reduction. To guarantee equal access to educational opportunities, ethical issues pertaining to the use of student data and the possibility of algorithmic bias must be properly addressed. Moreover, the scalability of these customized systems has to be maximized to support a variety of learning environments as MOOCs spread around the world. For a worldwide audience, future research should concentrate on improving system scalability, honing customization strategies, and addressing ethical considerations in order to develop online learning platforms that are more equitable, inclusive, and productive.

References

[1] Y.-C. Chen, L. Hui, and T. Thaipisutikul, "A collaborative filtering recommendation system with dynamic time decay," *J. Supercomput.*, vol. 77, pp. 244–262, 2021.

[2] Y. Zhou, C. Huang, Q. Hu, J. Zhu, and Y. Tang, "Personalized learning full-path recommendation model based on LSTM neural networks," *Inf. Sci. (Ny).*, vol. 444, pp. 135–152, 2018.

[3] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," *Knowledge-based Syst.*, vol. 211, p. 106545, 2021.

[4] Q. Cui, S. Wu, Q. Liu, W. Zhong, and L. Wang, "MV-RNN: A multi-view recurrent neural network for sequential recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 32, no. 2, pp. 317–331, 2018.

[5] P. Symeonidis and D. Malakoudis, "Multi-modal matrix factorization with side information for recommending massive open online courses," *Expert Syst. Appl.*, vol. 118, pp. 261–271, 2019.

[6] Z. A. Pardos, S. Tang, D. Davis, and C. V. Le, "Enabling real-time adaptivity in MOOCs with a personalized next-step recommendation framework," in *Proceedings of the fourth (2017) ACM conference on learning@ scale*, 2017, pp. 23–32.

[7] P.-C. Chang, C.-H. Lin, and M.-H. Chen, "A hybrid course recommendation system by integrating collaborative filtering and artificial immune systems," *Algorithms*, vol. 9, no. 3, p. 47, 2016.

[8] J. Tang and K. Wang, "Personalized top-n sequential recommendation via convolutional sequence embedding," in *Proceedings of the eleventh ACM international conference on web search and data mining*, 2018, pp. 565–573.

[9] D. Wu, J. Lu, and G. Zhang, "A fuzzy tree matching-based personalized e-learning recommender system," *IEEE Trans. fuzzy Syst.*, vol. 23, no. 6, pp. 2412–2426, 2015.

[10] Y. Pang, W. Liu, Y. Jin, H. Peng, T. Xia, and Y. Wu, "Adaptive recommendation for MOOC with collaborative filtering and time series," *Comput. Appl. Eng. Educ.*, vol. 26, no. 6, pp. 2071–2083, 2018.

[11] Z. Huang, X. Xu, H. Zhu, and M. Zhou, "An efficient group recommendation model with multiattention-based neural networks," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 31, no. 11, pp. 4461–4474, 2020.

[12] S. Deng, L. Huang, G. Xu, X. Wu, and Z. Wu, "On deep learning for trust-aware recommendations in social networks," *IEEE Trans. neural networks Learn. Syst.*, vol. 28, no. 5, pp. 1164–1177, 2016.

[13] Y. Lin *et al.*, "A survey on reinforcement learning for recommender systems," *IEEE Trans. Neural Networks Learn. Syst.*, 2023.

[14] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Comput. Surv.*, vol. 52, no. 1, pp. 1–38, 2019.

[15] Z. Y. Khan, Z. Niu, S. Sandiwarno, and R. Prince, "Deep learning techniques for rating prediction: a survey of the state-of-the-art," *Artif. Intell. Rev.*, vol. 54, pp. 95–135, 2021.

[16] X. He, Z. He, J. Song, Z. Liu, Y.-G. Jiang, and T.-S. Chua, "NAIS: Neural attentive item similarity model for recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 30, no. 12, pp. 2354–2366, 2018.

[17] F. Bousbahi and H. Chorfi, "MOOC-Rec: a case based recommender system for MOOCs," *Procedia-Social Behav. Sci.*, vol. 195, pp. 1813–1822, 2015.

[18] X. Jing and J. Tang, "Guess you like: course recommendation in MOOCs," in *Proceedings of the international conference on web intelligence*, 2017, pp. 783–789.

[19] X. Li, X. Li, J. Tang, T. Wang, Y. Zhang, and H. Chen, "Improving deep item-based collaborative filtering with Bayesian personalized ranking for MOOC course recommendation," in *Knowledge Science, Engineering and Management: 13th International Conference, KSEM 2020, Hangzhou, China, August 28–30, 2020, Proceedings, Part I 13*, Springer, 2020, pp. 247–258.

[20] J. Li, P. Ren, Z. Chen, Z. Ren, T. Lian, and J. Ma, "Neural attentive session-based recommendation," in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 2017, pp. 1419–1428.

[21] J. Zhang, B. Hao, B. Chen, C. Li, H. Chen, and J. Sun, "Hierarchical reinforcement learning for course recommendation in MOOCs," in *Proceedings of the AAAI conference on artificial intelligence*, 2019, pp. 435–442.

[22] K. K. Jena *et al.*, "E-learning course recommender system using collaborative filtering models," *Electronics*, vol. 12, no. 1, p. 157, 2022.

[23] S. Amin, M. I. Uddin, H. H. Al-Baity, M. A. Zeb, M. A. Khan, and M. A. Khan, "Machine learning approach for COVID-19 detection on twitter," *Comput. Mater. Contin.*, vol. 68, no. 2, pp. 2231–2247, 2021.

[24] J. L. Martin, H. A. Salvatierra, and J. R. H. González, "MOOCs for all: Evaluating the accessibility of top MOOC platforms," *Int. J. Eng. Educ.*, vol. 32, no. 5, pp. 2274–2283, 2016.

[25] E. Aeiad and F. Meziane, "An adaptable and personalised E-learning system applied to computer science Programmes design," *Educ. Inf. Technol.*, vol. 24, no. 2, pp. 1485–1509, 2019.

[26] S. Assami, D. Najima, and R. Ajhoun, "Implementation of a Machine Learning-Based MOOC Recommender System Using Learner Motivation Prediction," *Int. J. Eng. Pedagog.*, vol. 12, pp. 68–85, Nov. 2022, doi: 10.3991/ijep.v12i5.30523.

[27] S. Tang, "Learning mechanism and function characteristics of MOOC in the process of higher education," *Eurasia J. Math. Sci. Technol. Educ.*, vol. 13, no. 12, pp. 8067–8072, 2017.

[28] E. Ayub and L. C. Leong, "Developing a pedagogy framework for institution-wide implementation of MOOC: A case study from a Malaysian Private University," *Adv. Sci. Lett.*, vol. 23, no. 2, pp. 809–813, 2017.

[29] P. Guo, "MOOC and SPOC, which one is better?," *Eurasia J. Math. Sci. Technol. Educ.*, vol. 13, no. 8, pp. 5961–5967, 2017.

[30] H. Zhang, T. Huang, Z. Lv, S. Liu, and H. Yang, "MOOCRC: A highly accurate resource recommendation model for use in MOOC environments," *Mob. Networks Appl.*, vol. 24, pp. 34–46, 2019.

[31] K. Mingsiritham and G. Chanyawudhiwan, "Experiment of the prototype of online learning resources on massive open online course (mooc) to develop life skills in using technology media for hearing impaired students," *Int. J. Emerg. Technol. Learn.*, vol. 15, no. 3, pp. 242–249, 2020.

[32] H. Zhang, T. Huang, Z. Lv, S. Liu, and Z. Zhou, "MCRS: A course recommendation system for MOOCs," *Multimed. Tools Appl.*, vol. 77, pp. 7051–7069, 2018.

[33] A. Khalid, K. Lundqvist, and A. Yates, "Recommender systems for MOOCs: A systematic literature survey (January 1, 2012–July 12, 2019)," *Int. Rev. Res. Open Distrib. Learn.*, vol. 21, no. 4, pp. 255–291, 2020.

[34] P. Zhang, Z. Zhang, T. Tian, and Y. Wang, "Collaborative filtering recommendation algorithm integrating time windows and rating predictions," *Appl. Intell.*, vol. 49, no. 8, pp. 3146–3157, 2019.

[35] J. Shu, X. Shen, H. Liu, B. Yi, and Z. Zhang, "A content-based recommendation algorithm for learning resources," *Multimed. Syst.*, vol. 24, no. 2, pp. 163–173, 2018.

[36] J. Xiao, M. Wang, B. Jiang, and J. Li, "A personalized recommendation system with combinational algorithm for online learning," *J. Ambient Intell. Humaniz. Comput.*, vol.

9, pp. 667–677, 2018.

[37] T. Liu, Q. Wu, L. Chang, and T. Gu, "A review of deep learning-based recommender system in e-learning environments," *Artif. Intell. Rev.*, vol. 55, no. 8, pp. 5953–5980, 2022.

[38] E. U. Okon, B. O. Eke, and P. O. Asagba, "An improved online book recommender system using collaborative filtering algorithm," *Int. J. Comput. Appl.*, vol. 179, no. 46, pp. 41–48, 2018.

[39] L. N. Tondji, "Web recommender system for job seeking and recruiting," *Partial Fulfillment a Masters II AIMS*, 2018.

[40] M. D. Dixson, "Measuring student engagement in the online course: The Online Student Engagement scale (OSE).," *Online Learn.*, vol. 19, no. 4, p. n4, 2015.

[41] E. F. Barkley and C. H. Major, *Student engagement techniques: A handbook for college faculty*. John Wiley & Sons, 2020.

[42] J. Lee, H.-D. Song, and A. J. Hong, "Exploring factors, and indicators for measuring students' sustainable engagement in e-learning," *Sustainability*, vol. 11, no. 4, p. 985, 2019.

[43] M. D. Dixson, M. R. Greenwell, C. Rogers-Stacy, T. Weister, and S. Lauer, "Nonverbal immediacy behaviors and online student engagement: Bringing past instructional research into the present virtual classroom," *Commun. Educ.*, vol. 66, no. 1, pp. 37–53, 2017.

[44] M. Hussain, W. Zhu, W. Zhang, and S. M. R. Abidi, "Student Engagement Predictions in an e-Learning System and Their Impact on Student Course Assessment Scores," *Comput. Intell. Neurosci.*, vol. 2018, no. 1, p. 6347186, 2018.

[45] P. J. Guo, J. Kim, and R. Rubin, "How video production affects student engagement: An empirical study of MOOC videos," in *Proceedings of the first ACM conference on Learning@ scale conference*, 2014, pp. 41–50.

[46] A. Pardo, F. Han, and R. A. Ellis, "Exploring the relation between self-regulation, online activities, and academic performance: A case study," in *Proceedings of the sixth international conference on learning analytics & knowledge*, 2016, pp. 422–429.

[47] J. Mutahi, A. Kinai, N. Bore, A. Diriye, and K. Weldemariam, "Studying engagement and performance with learning technology in an African classroom," in *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 2017, pp. 148–152.

[48] J. Gaytan and B. C. McEwen, "Effective online instructional and assessment strategies," *Am. J. Distance Educ.*, vol. 21, no. 3, pp. 117–132, 2007.

[49] P. Lévy and N. Wakabayashi, "User's appreciation of engagement in service design: The case of food service design," in *Proceedings of International Service Innovation Design Conference 2008-ISIDC08*, 2008.

[50] J. S. Liang, "The effects of learning styles and perceptions on application of interactive learning guides for web-based courses," in *23rd annual conference of the Australasian Association for Engineering Education 2012: Profession of engineering education:*

Advancing teaching, research and careers, Engineers Australia [Melbourne, Vic.], 2012, pp. 712–721.

[51] S. Evans, J. Steele, S. Robertson, and T. Dyer, "Personalizing Post Titles in the Online Classroom: A Best Practice?.," *J. Educ. Online*, vol. 14, no. 2, p. n2, 2017.

[52] S. Hong, "Developing competency model of learners in distance universities," *J. Educ. Technol.*, vol. 25, no. 4, pp. 157–186, 2009.

[53] L. M. Nkomo, B. K. Daniel, and R. J. Butson, "Synthesis of student engagement with digital technologies: a systematic review of the literature," *Int. J. Educ. Technol. High. Educ.*, vol. 18, pp. 1–26, 2021.

[54] D. Verpoorten, C. Glahn, M. Kravcik, S. Ternier, and M. Specht, "Personalisation of learning in virtual learning environments," in *Learning in the Synergy of Multiple Disciplines: 4th European Conference on Technology Enhanced Learning, EC-TEL 2009 Nice, France, September 29–October 2, 2009 Proceedings 4*, Springer, 2009, pp. 52–66.

[55] M. Baguley *et al.*, *Educational learning and development: Building and enhancing capacity*. Springer, 2014.

[56] A. Klašnja-Milićević *et al.*, "Personalization and adaptation in e-learning systems," *E-Learning Syst. Intell. Tech. Pers.*, pp. 21–25, 2017.

[57] F. Essalmi, L. J. Ben Ayed, M. Jemni, and S. Graf, "Generalized metrics for the analysis of E-learning personalization strategies," *Comput. Human Behav.*, vol. 48, pp. 310–322, 2015.

[58] G. Paquette, O. Mariño, D. Rogozan, and M. Léonard, "Competency-based personalization for massive online learning," *Smart Learn. Environ.*, vol. 2, pp. 1–19, 2015.

[59] F. Essalmi, L. J. Ben Ayed, M. Jemni, and S. Graf, "A fully personalization strategy of E-learning scenarios," *Comput. Human Behav.*, vol. 26, no. 4, pp. 581–591, 2010.

[60] C. Alario Hoyos, M. Pérez Sanagustín, D. Cormier, and C. Delgado Koos, "Proposal for a conceptual framework for educators to describe and design MOOCs," 2014.

[61] N. Bansal, "Adaptive recommendation system for MOOC," *Indian Inst. Technol.*, pp. 1–40, 2013.

[62] I. Gutiérrez-Rojas, D. Leony, C. Alario-Hoyos, M. Pérez-Sanagustín, and C. Delgado-Kloos, "Towards an Outcome-based Discovery and Filtering of MOOCs using moocrank," *Proc. Second MOOC Eur. Stakeholders Summit*, pp. 50–57, 2014.

[63] N. Sonwalkar, "The first adaptive MOOC: A case study on pedagogy framework and scalable cloud Architecture—Part I," in *MOOCs forum*, Mary Ann Liebert, Inc. 140 Huguenot Street, 3rd Floor New Rochelle, NY 10801 USA, 2013, pp. 22–29.

[64] A. Amory, K. Naicker, J. Vincent, and C. Adams, "The use of computer games as an educational tool: identification of appropriate game types and game elements," *Br. J. Educ. Technol.*, vol. 30, no. 4, pp. 311–321, 1999.

[65] A. Iftene and J. Vanderdonckt, "Moocbuddy: a chatbot for personalized learning with moocs," in *RoCHI–International Conference on Human-Computer Interaction*, 2016, p.

91.

[66] H. Chorfi and M. Jemni, “PERSO: Towards an adaptive e-learning system,” *J. Interact. Learn. Res.*, vol. 15, no. 4, pp. 433–447, 2004.

[67] F. Celli, A. Ghosh, F. Alam, and G. Riccardi, “In the mood for sharing contents: Emotions, personality and interaction styles in the diffusion of news,” *Inf. Process. Manag.*, vol. 52, no. 1, pp. 93–98, 2016.

[68] D. Milosevic, M. Brkovic, and D. Bjekic, “Designing lesson content in adaptive learning environments,” *Int. J. Emerg. Technol. Learn.*, vol. 1, no. 2, pp. 1–9, 2006.

[69] P. Honey and A. Mumford, *The manual of learning styles*. Peter Honey, 1986.

[70] R. M. Felder, “Learning and teaching styles in engineering education,” 2002.

[71] G. Le Bouedec, “Les études doctorales en sciences de l’éducation: Pour un accompagnement personnalisé des mémoires et des thèses,” 1985.

[72] N. Stash, A. Cristea, and P. De Bra, “Adaptation to learning styles in e-learning: Approach evaluation,” in *E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, Association for the Advancement of Computing in Education (AACE), 2006, pp. 284–291.

[73] S. Graf, “Considering Cognitive Traits and Learning Styles to Open Web-Based Learning to a Larger Student Community,” 2007.

[74] F. Essalmi, L. J. Ben Ayed, and M. Jemni, “A multi-parameters personalization approach of learning scenarios,” in *Seventh IEEE International Conference on Advanced Learning Technologies (ICALT 2007)*, IEEE, 2007, pp. 90–91.

[75] A. A. Qaffas, K. Kaabi, R. Shadiev, and F. Essalmi, “Towards an optimal personalization strategy in MOOCs,” *Smart Learn. Environ.*, vol. 7, no. 1, p. 14, 2020.

[76] J. Kay, P. Reimann, E. Diebold, and B. Kummerfeld, “MOOCs: So many learners, so much potential...,” *IEEE Intell. Syst.*, vol. 28, no. 3, pp. 70–77, 2013.

[77] H. Khalil and M. Ebner, “MOOCs completion rates and possible methods to improve retention-A literature review,” *EdMedia+ Innov. Learn.*, pp. 1305–1313, 2014.

[78] K. R. Koedinger, J. Kim, J. Z. Jia, E. A. McLaughlin, and N. L. Bier, “Learning is not a spectator sport: Doing is better than watching for learning from a MOOC,” in *Proceedings of the second (2015) ACM conference on learning@ scale*, 2015, pp. 111–120.

[79] L. Deslauriers, E. Schelew, and C. Wieman, “Improved learning in a large-enrollment physics class,” *Science (80-.).*, vol. 332, no. 6031, pp. 862–864, 2011.

[80] C. E. Wieman, “Large-scale comparison of science teaching methods sends clear message,” *Proc. Natl. Acad. Sci.*, vol. 111, no. 23, pp. 8319–8320, 2014.

[81] C. Brooks, R. M. Quintana, H. Choi, C. Quintana, T. NeCamp, and J. Gardner, “Towards culturally relevant personalization at scale: Experiments with data science learners,” *Int. J. Artif. Intell. Educ.*, vol. 31, pp. 516–537, 2021.

[82] R. F. Kizilcec, G. M. Davis, and G. L. Cohen, “Towards equal opportunities in MOOCs:

affirmation reduces gender & social-class achievement gaps in China," in *Proceedings of the fourth (2017) ACM conference on learning@ scale*, 2017, pp. 121–130.

[83] E. Sutrisno *et al.*, "Design of half-mode substrate integrated cavity inspired dual-band antenna," *IEEE Access*, vol. 2, no. 1, pp. 1–6, Jan. 2020, doi: 10.1007/978-3-031-09835-2_16.

[84] H. Yu, C. Miao, C. Leung, and T. J. White, "Towards AI-powered personalization in MOOC learning," *npj Sci. Learn.*, vol. 2, no. 1, p. 15, 2017.

[85] A. S. Sunar, N. A. Abdullah, S. White, and H. C. Davis, "Personalisation of MOOCs: The state of the art," 2015.

[86] Y. Dai, Y. Asano, and M. Yoshikawa, "Course Content Analysis: An Initiative Step toward Learning Object Recommendation Systems for MOOC Learners.," *Int. Educ. Data Min. Soc.*, 2016.

[87] H. Hajri, Y. Bourda, and F. Popineau, "Personalized recommendation of open educational resources in MOOCs," in *Computer Supported Education: 10th International Conference, CSEDU 2018, Funchal, Madeira, Portugal, March 15–17, 2018, Revised Selected Papers 10*, Springer, 2019, pp. 166–190.

[88] A. Ewais and D. A. Samra, "Adaptive MOOCs: A framework for adaptive course based on intended learning outcomes," in *2017 2nd International Conference on Knowledge Engineering and Applications (ICKEA)*, IEEE, 2017, pp. 204–209.

[89] Y. Rosen *et al.*, "The effects of adaptive learning in a massive open online course on learners' skill development," in *Proceedings of the fifth annual acm conference on learning at scale*, 2018, pp. 1–8.

[90] A. Pardo, J. Jovanovic, S. Dawson, D. Gašević, and N. Mirriahi, "Using learning analytics to scale the provision of personalised feedback," *Br. J. Educ. Technol.*, vol. 50, no. 1, pp. 128–138, 2019.

[91] Z. Wang *et al.*, "Educational question mining at scale: Prediction, analysis and personalization," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2021, pp. 15669–15677.

[92] S. Amin, M. I. Uddin, A. A. Alarood, W. K. Mashwani, A. O. Alzahrani, and H. A. Alzahrani, "An adaptable and personalized framework for top-N course recommendations in online learning," *Sci. Rep.*, vol. 14, no. 1, p. 10382, 2024.

[93] J. Shin and O. Bulut, "Building an intelligent recommendation system for personalized test scheduling in computerized assessments: A reinforcement learning approach," *Behav. Res. Methods*, vol. 54, no. 1, pp. 216–232, 2022.

[94] W. Lyu, Y. Huang, and J. Liu, "The multifaceted influence of multidisciplinary background on placement and academic progression of faculty," *Humanit. Soc. Sci. Commun.*, vol. 11, no. 1, pp. 1–21, 2024.

[95] Z. Shahbazi and Y.-C. Byun, "Agent-based recommendation in E-learning environment using knowledge discovery and machine learning approaches," *Mathematics*, vol. 10, no. 7, p. 1192, 2022.

[96] G. Zheng *et al.*, "DRN: A deep reinforcement learning framework for news

recommendation," in *Proceedings of the 2018 world wide web conference*, 2018, pp. 167–176.

[97] Z. Yuyan, S. Xiayao, and L. Yong, "A novel movie recommendation system based on deep reinforcement learning with prioritized experience replay," in *2019 IEEE 19th International Conference on Communication Technology (ICCT)*, IEEE, 2019, pp. 1496–1500.

[98] L. Huang, M. Fu, F. Li, H. Qu, Y. Liu, and W. Chen, "A deep reinforcement learning based long-term recommender system," *Knowledge-based Syst.*, vol. 213, p. 106706, 2021.

[99] Y. Lin *et al.*, "Hierarchical reinforcement learning with dynamic recurrent mechanism for course recommendation," *Knowledge-Based Syst.*, vol. 244, p. 108546, 2022.

[100] N. Vedavathi and A. K. KM, "E-learning course recommendation based on sentiment analysis using hybrid Elman similarity," *Knowledge-Based Syst.*, vol. 259, p. 110086, 2023.

[101] Y. Liu, Y. Dong, C. Yin, C. Chen, and R. Jia, "A personalized course recommendation model integrating multi-granularity sessions and multi-type interests," *Educ. Inf. Technol.*, vol. 29, no. 5, pp. 5879–5901, 2024.

[102] Y. Zhu, H. Lu, P. Qiu, K. Shi, J. Chambua, and Z. Niu, "Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization," *Neurocomputing*, vol. 415, pp. 84–95, 2020.

[103] R. Campos, R. P. dos Santos, and J. Oliveira, "Providing recommendations for communities of learners in MOOCs ecosystems," *Expert Syst. Appl.*, vol. 205, p. 117510, 2022.

[104] M. Nilashi *et al.*, "Knowledge discovery for course choice decision in Massive Open Online Courses using machine learning approaches," *Expert Syst. Appl.*, vol. 199, p. 117092, 2022.

[105] L. Boratto, G. Fenu, and M. Marras, "The effect of algorithmic bias on recommender systems for massive open online courses," in *European conference on information retrieval*, Springer, 2019, pp. 457–472.

[106] Y. Lin, S. Feng, F. Lin, W. Zeng, Y. Liu, and P. Wu, "Adaptive course recommendation in MOOCs," *Knowledge-Based Syst.*, vol. 224, p. 107085, 2021.

[107] J. Wang, H. Xie, F. L. Wang, L.-K. Lee, and O. T. S. Au, "Top-N personalized recommendation with graph neural networks in MOOCs," *Comput. Educ. Artif. Intell.*, vol. 2, p. 100010, 2021.

[108] Y. Lin, F. Lin, L. Yang, W. Zeng, Y. Liu, and P. Wu, "Context-aware reinforcement learning for course recommendation," *Appl. Soft Comput.*, vol. 125, p. 109189, 2022.

[109] Y. Madani, H. Ezzikouri, M. Erritali, and B. Hssina, "Finding optimal pedagogical content in an adaptive e-learning platform using a new recommendation approach and reinforcement learning," *J. Ambient Intell. Humaniz. Comput.*, vol. 11, pp. 3921–3936, 2020.

Vol. 22, No. 1, (2025)
ISSN: 1005-0930