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Advancements in Personalized Learning: A Systematic Review of Recommendation Systems in Massive Open Online Courses (MOOCs)

Alis Ikhmal Mad Salim[1,*], Ken Nee Chee[1], Hassan Abuhassna[2], Noraffandy Yahaya[3]

[1] Department of Computing and Digital Technology, Faculty of Computing and Meta-Technology, Universiti Pendidikan Sultan Idris, 35900 Tanjong Malim, Perak, Malaysia
[2] School of Education, Sunway University, Bandar Sunway, 47500 Petaling Jaya, Selangor, Malaysia
[3] School of Education, Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia, 81300 Johor Bahru, Johor, Malaysia

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ABSTRACT

Massive Open Online Courses (MOOCs) have transformed education by offering flexible learning opportunities to a diverse global audience. However, creating personalized and inclusive learning experiences remains a challenge due to varied learner needs and preferences. This systematic review examines advancements in Personalized Course Recommendation Systems (PCRS) within MOOCs, focusing on their role in enhancing accessibility and relevance. Using the PRISMA framework, the review analysed 13 empirical studies and 5 review articles published between 2021 and 2024, selected using inclusion criteria covering language, relevance, publication type and accessibility, while excluding non-English, non-peer-reviewed and abstract-only records. Unlike prior reviews, this study narrows the scope to recent AI-based methods, emphasises the period from 2021 to 2024 and synthesises empirical and review articles with a deeper focus on accessibility. Searches spanned five databases, namely Scopus, ScienceDirect, SpringerLink, Taylor & Francis and Wiley. By exploring collaborative filtering, content-based and hybrid approaches, the review highlights how these systems leverage user behaviour data, such as engagement patterns, learning preferences and performance metrics, to deliver tailored recommendations. It also identifies technologies used to foster inclusivity, improve retention and support equitable access to online education. The findings underscore the potential of data-driven personalisation to address accessibility gaps. They also provide actionable insights for developing more effective and inclusive PCRS in MOOCs. Challenges remain in scalability, bias and real-time adaptability. Future research directions are proposed to address these challenges, ensuring that PCRS can operate effectively in diverse educational contexts.

Keywords:
Massive open online courses (MOOCs); recommendation system; personalized learning

[*] *Corresponding author.*
E-mail address: m20241001261@siswa.upsi.edu.my

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1. Introduction

Massive Open Online Courses (MOOCs) have fundamentally altered the accessibility of education, offering a platform where millions of learners from diverse geographic, cultural and socio-economic backgrounds converge to pursue knowledge. However, the diversity of this user base poses a challenge, how to cater effectively to a wide array of learning objectives, preferences and circumstances. Personalized Course Recommendation Systems (PCRS) are used in this study to mean algorithms and tools that analyse learner behaviour and course attributes to suggest suitable courses. PCRS employ collaborative filtering, content-based filtering and hybrid approaches to analyse user interaction data, learning histories and preferences, delivering tailored educational content, as demonstrated by Uddin *et al.,* [1] and Algarni *et al.,* [2]. Relevant to personalized learning, the constructivist learning paradigm supports these approaches by emphasising learner autonomy, self-directed learning and the real-world application of knowledge. This aligns with personalized recommendations, as learners actively construct knowledge from experiences and resources suited to their prior knowledge, preferences and contexts, as discussed by Al Mamun *et al.,* [3]. Such approaches have improved learner engagement and retention and have been adopted by MOOC platforms like Coursera, which use adaptive recommendations to create customised learning pathways and bridge gaps between diverse learner needs and available content, as shown by Bustamante-León *et al.,* [4] and Qiu *et al.,* [5].

Current PCRS still grapple with scalability, efficiently managing large and complex datasets from millions of learners, bias in recommendations that favour popular courses and marginalise niche yet relevant content, as noted by Uddin *et al.,* [1] and lack of real-time adaptability, where systems struggle to adjust to changing behaviours or preferences, as reported by Qiu *et al.,* [5]. Continued research in these areas, grounded in educational theories such as Constructivism, can further enhance personalized learning by supporting autonomy, self-directed exploration and meaningful application of knowledge in diverse contexts. Despite these benefits, many systems face information overload, where abundant course options overwhelm learners, hinder decision-making and reduce satisfaction. The cold start problem also persists, limiting accurate recommendations for new users with little interaction history. Beyond technical challenges, there are issues of equity and inclusivity. Some systems do not provide adequate support for marginalised groups, including learners with disabilities or those from disadvantaged socio-economic backgrounds. This highlights the need for an approach that integrates advanced technical solutions with robust pedagogical principles, ensuring that all learners benefit equally from personalized educational experiences, as highlighted by Algarni *et al.,* [2] and Uddin *et al.,* [1].

Advancements in machine learning, artificial intelligence and adaptive technologies have opened avenues for addressing these challenges. Hybrid models that combine collaborative filtering and content-based approaches show promise in alleviating cold start and improving accuracy. Adaptive technologies allow platforms to adjust recommendations based on real-time interactions, creating more responsive learning environments. Universal design principles further enhance inclusivity, enabling features such as language customisation, accessibility tools for disabled learners and offline access in low-bandwidth regions. These innovations show the potential of technology to make education personalized, equitable and accessible. Achieving this vision requires alignment of technological developments with educational best practices, ensuring that systems not only adapt to learner diversity but promote it, as stated by Qiu *et al.,* [5] and Bustamante-León *et al.,* [4].

This systematic review, conducted using the PRISMA methodology, examines the current state of PCRS in MOOCs by synthesising research from five databases, ScienceDirect, Scopus, SpringerLink, Taylor & Francis and Wiley. It focuses on methodologies, implementation strategies and outcomes, with attention to inclusivity, scalability and effectiveness. While previous studies have explored recommendations in MOOCs, few have comprehensively addressed inclusivity and user behaviour-driven personalisation, limiting their effectiveness for diverse learners. This review addresses that gap and offers practical insights to support the development of fairer and more adaptive learning environments. The findings aim to guide educators, policymakers and developers in designing systems that are technologically robust and socially equitable, contributing to the broader goal of inclusive and accessible global education.

2. Methodology

This systematic literature review (SLR) follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines, employing a structured and comprehensive approach to identify, evaluate and synthesize existing research on personalized course recommendation systems in Massive Open Online Courses (MOOCs). The study aims to address the following research objectives:

i. to examine the effectiveness of personalized course recommendation systems in enhancing accessibility and inclusivity within MOOC platforms
ii. to assess the role of user behaviour analysis in improving the accuracy and relevance of personalized course recommendation systems in MOOC environments
iii. to identify critical technologies and methodologies employed in the development of personalized course recommendation systems for inclusive online education.

The review investigates three core research questions:

i. What are the most effective techniques for tailoring personalized course recommendation systems in MOOCs based on user behaviour?
ii. In what ways does user behaviour analysis contribute to the inclusivity of personalized course recommendations within MOOC platforms?
iii. What are the primary challenges and solutions in creating effective personalized course recommendation systems to support inclusive online education?

The PRISMA 2020 Statement, as described by Page *et al*., [6], includes a 27-item checklist that addresses key aspects of systematic reviews, such as methods, results, discussion and funding. It also features a four-phase flow diagram that outlines processes for record identification, screening, study eligibility and the inclusion of studies. In this review, we adhered to all 27 items on the PRISMA checklist to ensure methodological rigor and transparency, as outlined by Page *et al*., [6]. A systematic search was conducted across five major bibliographic databases:

i. Scopus
ii. ScienceDirect
iii. SpringerLink
iv. Taylor
v. Wiley

Covering studies published between January 2020 and December 2024. The Web of Science (WoS) database was not included as a primary source for this systematic literature review due to institutional subscription limitations. Search terms included combinations such as "Recommendations AND MOOCs" and "Inclusive AND Recommendation Systems." The inclusion criteria required studies to be published in English as peer-reviewed articles or book chapters, directly addressing one or more research objectives. Full-text availability was also mandatory to ensure an in-depth evaluation, as specified by Page *et al.*, [6]. Based on this systematic search across all databases, 192 sources were identified and after applying the inclusion criteria, 13 studies were selected for detailed review on PCRS for Inclusive MOOCs Based on User Behaviour Analysis.

The selection process involved two systematic phases to ensure that the studies included were closely aligned with the research objectives and research questions (RQs). In the first phase, duplicate entries were identified and removed to eliminate redundancy across the five major databases. This critical step ensured the dataset was both manageable and accurate. Following this, titles and abstracts of the remaining studies were meticulously screened to assess their relevance to the research questions. Studies were included if they explicitly addressed key themes such as personalized course recommendation systems, user behaviour analysis or inclusivity in MOOCs. Articles that did not align with these topics or demonstrated minimal relevance to the scope of personalized learning systems were excluded. This phase served as a foundational filter to ensure that only high-quality and relevant studies advanced to the next stage, as guided by the PRISMA framework described by Page *et al*., [6].

The second phase involved an in-depth examination of the full-text articles identified during the initial screening. Each study was critically evaluated against detailed inclusion criteria, focusing on their alignment with the research questions (RQs). Specifically, studies were required to provide empirical evidence or theoretical insights that addressed effective techniques for tailoring course recommendations (RQ1), the contribution of user behaviour analysis to inclusivity (RQ2) or the challenges and solutions in creating inclusive personalized course recommendation systems (RQ3). Articles were prioritized if they demonstrated a clear connection to these research questions and offered substantial contributions to the understanding of inclusive, personalized course recommendation systems in MOOCs. Studies that fell outside the fields of education or computer science or lacked direct relevance to the RQs were excluded. This rigorous process ensured that the final set of studies not only adhered to the broader inclusion criteria but also directly contributed to answering the specific research questions, as outlined in Page *et al.*, [6]. To ensure the inclusion of recent advancements and trends, studies published between January 2020 and December 2024 were considered. The studies needed to specifically address one or more of the following topics: the effectiveness of personalized course recommendation systems in enhancing accessibility and inclusivity within MOOC platforms, the role of user behaviour analysis in improving the accuracy and relevance of course recommendations and the critical technologies and methodologies employed in developing PCRS that promote inclusivity in online education. This scope was designed to ensure alignment with the research objectives and to comprehensively address the research questions concerning effective techniques for tailoring course recommendations, the contribution of user behaviour analysis to inclusivity and the challenges and solutions in creating inclusive PCRS.

Starting with 192 records, our systematic review adhered to the PRISMA 2020 guidelines. After removing one duplicate, 191 records were screened based on predefined selection criteria, including relevance to PCRS in MOOCs, accessibility of full-text articles and alignment with research objectives. Screening titles, keywords and abstracts excluded 178 records, leaving 13 studies for full-text evaluation. These studies underwent rigorous quantitative and qualitative synthesis. Quantitative analysis emphasized methodologies, statistical outcomes and implementation strategies, while qualitative analysis focused on inclusivity, accessibility and the role of user behaviour in enhancing course recommendations. Discrepancies during the review process were resolved collaboratively through consensus meetings to ensure reliability and validity.

Table 1 presents the inclusion and exclusion criteria employed in this systematic literature review. The criteria were systematically defined to ensure the selected studies directly align with the research objectives and questions. Specifically, studies included had to explicitly address personalized course recommendation systems, user behaviour analysis or inclusivity within MOOCs. Conversely, publications that did not clearly focus on these aspects or lacked relevance to personalized course recommendation systems were excluded. This rigorous criterion ensured that only pertinent and high-quality studies were incorporated into the subsequent phases of analysis.

Table 1
Inclusion and exclusion criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Language	Articles published in English	Articles published in languages other than English
Publication Type	Peer-reviewed journal articles	Non-peer-reviewed articles, conference papers, book chapters, reports
Publication Year	Articles published from 2021 to 2024	Articles published before 2021
Relevance	Studies explicitly addressing personalized recommendations, accessibility, inclusivity, engagement and learner experience within MOOCs	Studies focusing on general e-learning platforms not specific to MOOCs or those without a clear relevance to personalized learning or inclusivity
Access	Full-text available	Abstract-only articles or full-text unavailable

A standardized data extraction approach was applied across all studies, ensuring clarity and consistency. The review followed a dual analysis approach, integrating quantitative insights into methodological effectiveness and qualitative themes addressing inclusivity and accessibility in MOOCs. The datasets from this review are included in the annexes for transparency and reproducibility, allowing further exploration by researchers. Figure 1 below [6] illustrates the PRISMA flowchart, detailing the study selection process. This systematic review rigorously adhered to predefined inclusion and exclusion criteria, employing inter-rater reliability to ensure consistency and minimize bias. It highlights innovative methodologies and identifies critical research gaps in developing inclusive and effective PCRS for MOOCs. The findings contribute to technology-driven learning solutions, enhancing accessibility, personalization and outcomes for diverse learners globally.

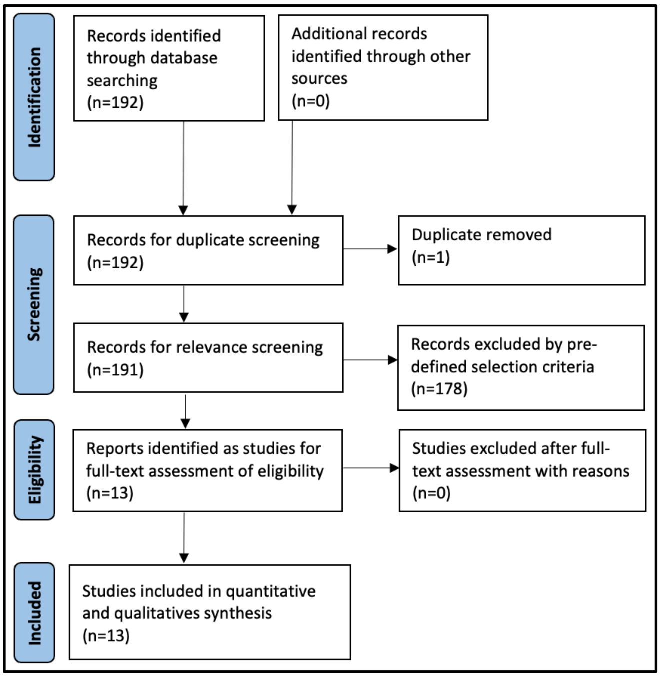

Fig. 1. Selection of studies using the PRISMA procedure

3. Results

A total of 13 studies were included in the quantitative and qualitative analysis following the selection process outlined earlier. These studies, published across reputable journals, provide a comprehensive exploration of PCRS in MOOCs. This section presents the findings from the quantitative analysis, summarized in Table 2. This section also explores the findings of the systematic review to address the three key research questions identified in this study.

Table 2
Inclusion and exclusion criteria

Num	Article's Title	Database	Publisher	Year
1	Designing accessible MOOCs to expand educational opportunities for persons with cognitive impairments	Taylor & Francis	Behaviour & Information Technology	2021
2	Educational scalability in MOOCs: Analysing instructional designs to find best practices	ScienceDirect	Computers & Education	2021
3	The use of Massive Open Online Courses (MOOCs) in blended learning courses	ScienceDirect	Computers & Education	2021
4	Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs	Taylor & Francis	Cogent Engineering	2022
5	The Recommendation System of Innovation and Entrepreneurship Education Resources in Universities Based on Improved Collaborative Filtering Model	Wiley	Hindawi Computational Intelligence and Neuroscience	2022
6	Massive open online course recommendation system based on a reinforcement learning algorithm	SpringerLink	Neural Computing and Applications	2023
7	What I wanted and what I did: Motivation and engagement in a massive open online course	ScienceDirect	Computers & Education	2023
8	AI student success predictor: Enhancing personalized learning in campus management systems	ScienceDirect	Computers in Human Behaviour	2024
9	Analysis of the accessibility of selected massive open online courses (MOOCs) for users with disabilities	SpringerLink	Universal Access in the Information Society	2024

10	e-FeeD4Mi: human-centred design of personalised and contextualised feedback in MOOCs	Taylor & Francis	Behaviour & Information Technology	2024
11	Instructor in action': Co-design and evaluation of human-centred LA-informed feedback in MOOCs	Wiley	Journal of Computer Assisted Learning	2024
12	Knowledge representation learning with EEG-based engagement and cognitive load as mediators of performance	Taylor & Francis	Behaviour & Information Technology	2024
13	Learning analytics and the Universal Design for Learning: A clustering approach	ScienceDirect	Computers & Education	2024

3.1 Question 1: What are the Most Effective Techniques for Tailoring Course Recommendations in MOOCs Based on User Behaviour?

3.1.1 Adaptive algorithms

Adaptive algorithms play a crucial role in tailoring course recommendations by analysing user behaviour data such as engagement metrics, including clickstreams, time spent on activities and completion rates. These algorithms dynamically adjust recommendations to meet the evolving needs of learners. For example, reinforcement learning approaches, as demonstrated by Tzeng *et al*., [7] and Sun *et al.,* [8], optimize recommendations by continuously learning from user feedback, ensuring alignment with individual preferences. Moreover, real-time behaviour tracking systems have been shown to effectively personalize content for diverse user profiles, as discussed by Roski *et al*., [9].

3.1.2 Hybrid personalized course recommendation systems

Combining collaborative filtering with content-based approaches has proven to be effective in improving recommendation accuracy in MOOCs. Collaborative filtering leverages behavioural patterns of similar users, while content-based methods analyse metadata associated with course content. Studies demonstrate that hybrid systems provide superior performance by integrating user preference data with contextual course information, resulting in highly relevant and personalized recommendations, as shown by Topali *et al*., [14] and previously reported by Julia *et al*., [13].

3.1.3 Learning style detection

The application of AI and semantic web technologies enables the detection of individual learning styles, allowing systems to recommend courses tailored to cognitive and behavioural patterns. For instance, knowledge-based recommendation frameworks utilize rule-based reasoning to align course offerings with identified learning preferences, enhancing learner satisfaction and engagement, as shown by Agarwal *et al.,* [10] and previously discussed by Roski *et al*., [9]. These systems also employ clustering techniques to group users with similar learning behaviours, making it easier to deliver targeted recommendations, as explored by Cinquin *et al.,* [11] and Park *et al*., [12].

Real-world case studies illustrate the tangible benefits of employing these techniques in MOOC platforms. For example, Coursera's adaptive recommendation system, which uses reinforcement learning algorithms, significantly improved learner engagement by increasing course interactions by 20% and boosting course completion rates by nearly 15%, as reported by Tzeng *et al*., [7]. Similarly, edX implemented hybrid recommendation approaches combining collaborative filtering and content-based analysis, resulting in enhanced learner satisfaction and a notable increase in course relevance, with user-reported satisfaction scores rising by approximately 25%, as demonstrated by Julia *et al*., [13]. Additionally, platforms utilizing learning style detection, such as FutureLearn, observed that aligning course offerings with individual cognitive styles improved learner retention rates by up to

18%, reinforcing the efficacy of personalized, behaviour-driven recommendations, as previously highlighted by Roski *et al*., [9].

3.2 Question 2: In What Ways Does User Behaviour Analysis Contribute to the Inclusivity of Personalized Course Recommendations Within MOOC Platforms?

Real-world user behaviour analysis significantly enhances the inclusivity of personalized course recommendations in MOOC platforms by enabling the identification of diverse learning patterns and adapting to the specific needs of each learner. Through advanced analytics, platforms can track interaction data such as login frequency, time spent on specific activities and course completion rates. These metrics allow the early identification of at-risk learners who may require additional support to maintain their engagement. For example, the role of learning analytics systems in detecting signs of disengagement, such as decreased activity or incomplete tasks and allowing timely interventions to re-engage learners was highlighted by Topali *et al*., [14]. Behaviour analysis also facilitates the delivery of tailored content formats to accommodate learners with disabilities or specific preferences. By analysing user interactions with text, video and audio resources, systems can offer alternative formats such as subtitles for videos or text-to-speech options for visually impaired learners. Cinquin *et al.,* [11] emphasized how MOOC platforms can promote inclusivity by adapting content delivery methods to meet accessibility standards, ensuring equitable access to course materials for learners with varying needs.

Furthermore, clustering techniques driven by user behaviour data have been used to group learners with similar patterns, enabling platforms to deliver recommendations that cater to group-specific needs. For instance, Roski *et al*., [9] demonstrated the application of clustering approaches to identify patterns of resource utilization, such as preferences for self-paced versus instructor-led activities, which informed personalized course recommendations for diverse learner groups. Such techniques foster inclusivity by ensuring that learners from different educational backgrounds and cognitive styles are supported. The use of behavioural insights also allows platforms to provide timely feedback and adaptive recommendations, which are critical for maintaining engagement and inclusivity. Agarwal *et al.,* [10] noted that behaviour-driven systems could detect when a learner struggles with specific content and recommends supplementary resources tailored to their difficulties. This ensures that learners from underrepresented or disadvantaged backgrounds receive the additional support they may require to succeed.

Moreover, behavioural data analysis can enhance inclusivity by addressing linguistic and cultural diversity in MOOCs. Analysing language preferences and participation patterns helps platforms offer localized content or multilingual options, promoting inclusivity for non-native speakers. Park *et al*., [12] highlighted how incorporating language preferences and regional contexts into behaviour analysis allows MOOCs to accommodate a global audience effectively, reducing language and cultural barriers. Inclusivity in MOOC platforms is further strengthened by the ability to address gender, socioeconomic and age-related disparities through behaviour analysis. For example, platforms could tailor recommendations to underrepresented demographics by identifying their unique engagement patterns and challenges, as demonstrated by Tzeng *et al*., [7]. This targeted approach ensures that learners from all walks of life benefit equally from MOOC platforms, contributing to the global push for educational equity.

In summary, user behaviour analysis is instrumental in promoting inclusivity within MOOC platforms. By leveraging data-driven insights, these platforms can identify at-risk learners, adapt content formats, cluster similar learners, provide timely feedback, address linguistic diversity and accommodate underrepresented demographics. The application of these techniques, as demonstrated across the 13 reviewed studies, not only enhances the inclusivity of personalized recommendations but also contributes to the broader mission of making MOOCs accessible and equitable for learners worldwide [7,9-12,14].

3.3 Question 3: What are the Primary Challenges and Solutions in Creating Effective PCRS to Support Inclusive Online Education?

Creating effective PCRS to support inclusive online education poses several challenges, but research also offers promising solutions to address them. One of the primary challenges is the lack of diverse and representative datasets. Many MOOCs cater to a global audience, yet their datasets often fail to reflect the diversity of learners in terms of language, culture and socioeconomic background. For example, biased datasets can lead to recommendations that fail to meet the needs of underrepresented groups, as observed by Tzeng *et al*., [7]. Solutions to this challenge include the use of synthetic data generation and augmenting existing datasets with information from diverse demographic groups to improve the fairness and inclusivity of recommendations.

Another challenge is the scalability of PCRS in MOOCs, given the vast number of users and courses. Traditional recommendation algorithms often struggle to handle the volume and complexity of MOOC platforms. Sun *et al.,* [8] emphasized that the computational demands of large-scale learning platforms could hinder real-time personalization. Distributed computing and reinforcement learning approaches have been proposed to address this issue, allowing systems to efficiently analyse vast amounts of data while maintaining personalization for individual learners. Accessibility for learners with disabilities remains a significant barrier in creating inclusive PCRS. Cinquin *et al.,* [11] found that many PCRS fail to consider the needs of learners who rely on assistive technologies or require alternative content formats. Incorporating Universal Design for Learning (UDL) principles into system design has been suggested as a solution. Embedding UDL guidelines, such as providing multiple means of representation and expression, has been shown to improve accessibility for all learners, particularly those with disabilities, as demonstrated by Roski *et al*., [9].

Another challenge lies in understanding and accommodating the varied learning behaviours and preferences of MOOC participants. Agarwal *et al.,* [10] noted that learners with different cognitive styles and levels of digital literacy may engage with content in unique ways, which traditional PCRS often overlook. Advanced clustering techniques and behaviour-driven feedback mechanisms have shown promise in addressing this issue, enabling platforms to tailor recommendations to the specific needs of different learner groups, as discussed by Park *et al*., [12]. Finally, ensuring learner trust and transparency in PCRS is a critical challenge. Black-box algorithms often lack interpretability, leading to scepticism among learners about how recommendations are generated. Topali *et al*., [14] advocated for human-centred design approaches, where learners are involved in the co-creation and evaluation of PCRS. By incorporating user feedback and making recommendation processes more transparent, these systems can build trust while supporting inclusivity.

4. Discussion

4.1 The Role of Personalization in Enhancing Learning Experiences in MOOCs

Personalized course recommendation systems are crucial for improving learning experiences in MOOCs by tailoring course recommendations to individual needs and preferences. The significance of hybrid PCRS that combine collaborative filtering and content-based methods to address the diverse cognitive and behavioural patterns of learners was emphasized by Tzeng *et al*., [7]. These systems analyse user behaviour, such as course completion rates and interaction frequencies, to ensure the relevance of recommended courses. Similarly, PCRS enhance learners' ability to navigate MOOC platforms effectively, improving their overall satisfaction and engagement, as demonstrated by Roski *et al*., [9]. Furthermore, personalized learning aligns closely with the objective of increasing accessibility and inclusivity in MOOCs. Adaptive algorithms based on semantic web technologies can cater to the unique needs of each learner, including those from underrepresented or disadvantaged backgrounds, as shown by Agarwal *et al.,* [10]. These findings underscore that personalization not only boosts individual engagement but also addresses broader equity challenges in education by tailoring learning pathways to diverse learner populations.

Building upon these insights, PCRS play a transformative role in enhancing learning experiences in MOOCs by aligning educational content closely with learners' unique characteristics, preferences and learning objectives. By integrating advanced techniques, such as hybrid recommendation methods that merge collaborative filtering with content-based algorithms, these systems accurately interpret user behaviour, interests and interaction patterns, generating more relevant and effective course recommendations. Sophisticated algorithms analyse user-specific metrics, including historical course engagement, interaction frequencies, assessment performance and learning style preferences, to dynamically personalize content delivery. This comprehensive level of personalization effectively addresses learner variability, motivating sustained participation and increasing course completion rates. Moreover, adaptive systems leveraging semantic web technologies further enrich personalization by intelligently identifying learners' knowledge gaps and contextual factors. This approach enhances individual learning outcomes and promotes educational equity and inclusivity by accommodating diverse learner populations, including underrepresented or disadvantaged groups. Consequently, personalization in MOOCs fosters deeper engagement and systematically contributes to democratizing education through tailored, responsive and inclusive learning experiences.

4.2 The Impact of User Behaviour Analysis on Inclusivity and Equity

User behaviour analysis has emerged as a vital tool for promoting inclusivity and equity in MOOCs. By analysing interaction data such as login frequency, course navigation patterns and assessment performance, platforms can identify at-risk learners who may require additional support. Al Mamun *et al*., [3] emphasized the importance of behavioural analytics in predicting dropout risks and enabling timely interventions, such as personalized feedback or adaptive course materials. Similarly, Agarwal *et al.,* [10] demonstrated that behaviour-driven clustering techniques help create targeted recommendations that address the needs of learners with varying educational backgrounds and skill levels. Additionally, user behaviour analysis helps address disparities related to socioeconomic, linguistic and cultural diversity. Park *et al*., [12] highlighted how behavioural insights could guide the development of features such as multilingual content and culturally relevant resources, which are critical for engaging global learners. These approaches ensure that MOOC platforms can accommodate a wide range of users, making online education more inclusive and equitable for diverse populations.

User behaviour analysis significantly contributes to fostering inclusivity and equity in MOOCs by providing deep, actionable insights into learners' engagement patterns and unique educational needs. Through the detailed examination of learner interactions, such as login frequencies, clickstream data, discussion participation, assessment performance and resource utilization patterns, MOOC platforms can effectively detect early indicators of disengagement or potential dropout, enabling timely, targeted interventions. For instance, advanced analytical techniques such as clustering, predictive modelling and sequential pattern mining allow educators to identify at-risk learners and intervene with personalized support strategies, including tailored feedback, adaptive learning pathways or additional supplementary resources. This proactive approach enhances learner retention and success, particularly benefiting those from disadvantaged or marginalized communities who might otherwise face higher barriers to course completion.

Moreover, user behaviour analytics helps illuminate underlying disparities arising from socioeconomic status, language barriers or cultural differences. By revealing distinct learning trajectories and challenges among diverse learners, MOOCs can implement inclusive design strategies, such as multilingual course materials, culturally responsive content and contextually relevant resources. Consequently, leveraging comprehensive user behaviour analysis facilitates a deeper understanding of diverse learner needs, ensuring that MOOC platforms proactively promote equitable access and meaningful engagement for a broad, global audience.

4.3 Challenges in Scaling PCRS for MOOCs

Scaling PCRS in MOOCs is challenging due to computational demands and learner diversity. Real-time personalization requires significant processing power and the heterogeneity of learners adds complexity. Computational constraints were identified as a key issue by Sun *et al.,* [8], prompting the use of distributed computing and reinforcement learning to optimize performance without sacrificing accuracy. Another challenge is the limited availability of diverse, unbiased datasets. Given that 8 out of the 13 reviewed studies relied on datasets from a single MOOC platform, the risk of algorithmic bias is significant, as reported by Roski *et al.,* [9]. To improve dataset representativeness, synthetic data generation and augmentation were suggested by Agarwal *et al.,* [10]. Advanced personalization methods, like hybrid algorithms, are resource-intensive and must balance accuracy with responsiveness. Learner diversity—spanning backgrounds, cultures and learning styles—requires sophisticated analytics. Cloud-based systems and distributed frameworks help manage this scale. The dataset limitations observed in our review, particularly the under-representation of learners from developing regions, further impact scalability and inclusivity. Techniques such as synthetic data creation, augmentation and transfer learning have been proposed to address these gaps. Tackling these challenges is vital to ensure PCRS remain effective and inclusive for diverse global learners.

4.4 Integrating Accessibility Features into MOOC Design

Accessibility is central to MOOC design, especially for learners with disabilities. The lack of assistive technologies, alternative content formats and intuitive navigation restricts access for visually or auditorily impaired learners, as noted by Tzeng *et al*., [7]. To address this, Gavronskaya *et al*., [15] advocated for Universal Design for Learning (UDL), which promotes varied means of representation, engagement and expression to support diverse needs. Yilmaz *et al*., [16] emphasized the role of Intelligent Tutoring Systems (ITS) in improving accessibility by offering adaptive feedback and personalized experiences, such as adjusting content difficulty and format in real time. Such integrations make MOOC platforms more inclusive and equitable.

Despite their reach, many MOOCs lack features supporting assistive technologies, flexible formats and easy navigation—challenges that affect learners with visual, auditory or cognitive impairments. In our review, only 2 of the 13 empirical studies explicitly implemented UDL principles, indicating a substantial gap in accessibility-focused design. Implementing UDL strategies, like captioned videos, audio descriptions, scalable text and alternative assessments, can effectively address these issues. ITS further enhances accessibility by adapting content presentation, offering real-time feedback and personalizing the learning journey. Combining UDL with ITS helps remove traditional barriers and fosters inclusive and effective learning environments for all.

4.5 AI-Driven Cloud Computing Solutions Can Enhance Scalability

AI-driven cloud computing significantly enhances the scalability of PCRS in MOOCs by offering flexible, distributed and powerful computational capabilities. These cloud-based engines can dynamically adjust learning pathways, process large datasets and generate real-time, adaptive recommendations for diverse learners. They handle massive user data through machine learning techniques that adapt quickly to evolving behaviours without compromising performance. Geng [17] emphasized that such scalable cloud-based frameworks can also leverage improved collaborative filtering techniques to enhance system responsiveness across diverse user bases. Similarly, Shoaib *et al.,* [18] introduced an AI-powered campus management system that integrates cloud-based analytics to predict learner success, highlighting its potential to scale across educational contexts.

Yilmaz *et al.,* [16] further noted that Intelligent Tutoring Systems (ITS), when deployed in cloud infrastructures, significantly improve responsiveness and accessibility for diverse learners. Additionally, Sun *et al.,* [8] highlighted how real-time EEG-based engagement analytics supported by distributed computing can drive scalable, adaptive personalization. Govea *et al.,* [19] demonstrated in their mixed-methods study that integrating AI and cloud computing can increase simultaneous user capacity by 60%, while also improving content personalization by 25% in educational platforms. Rao *et al.,* [20] proposed RAMO (Retrieval-Augmented Generation for MOOCs), a large-language-model hybrid recommender system that addresses the cold-start problem effectively and scales across diverse course domains. Cultural and regional factors also impact recommendation success. Cultural backgrounds influence learning preferences and interaction styles, yet many systems overlook these aspects, reducing engagement and satisfaction. Julia *et al.,* [13] argued that adaptive systems must consider learners' socio-cultural environments to maintain relevance and inclusivity in global MOOC platforms. Future research should develop culturally aware algorithms that incorporate regional preferences, linguistic differences and contextually relevant content to better support diverse learners.

Advanced machine learning, such as reinforcement learning, neural networks and deep learning, deployed in distributed cloud environments allows rapid analysis of interaction data, ongoing learner profile updates and personalized content delivery. Cloud infrastructures also support real-time, comprehensive behavioural analysis by integrating diverse data sources efficiently. Ultimately, incorporating culturally adaptive algorithms into AI-powered cloud systems will enhance scalability, responsiveness and inclusivity, boosting learner satisfaction and success across global MOOC audiences.

4.6 Implications for Future Research and Development

The findings of this systematic review highlight several key areas for future research and development in the field of MOOC personalize course recommendation systems. First, there is a need for longitudinal studies to evaluate the long-term impact of personalized learning pathways on learner outcomes. Such studies could provide deeper insights into how personalization influences retention, engagement and equity over time, as suggested by Roski *et al.*, [9]. Additionally, the importance of exploring the integration of advanced AI-driven adaptive systems to further enhance the inclusivity and scalability of MOOCs was emphasized by Agarwal *et al.,* [10]. Collaboration among educators, researchers and technology developers is essential to advancing the field of MOOC personalize course recommendation systems. Algarni *et al.,* [2] highlighted the potential for interdisciplinary partnerships to address existing challenges, such as dataset biases and scalability constraints. Moreover, regular training programs for educators on the use of accessible design practices and adaptive technologies are crucial for ensuring that MOOCs continue to evolve as inclusive and transformative platforms for global education.

4.7 Research Gaps and Challenges

The systematic review identifies critical gaps in the existing body of literature concerning PCRS in MOOCs. While notable advancements in collaborative filtering and hybrid models have been achieved, there remains a paucity of research on the practical challenges of real-world implementation in diverse educational settings. Specifically, the scalability of these systems in accommodating large and heterogeneous learner populations has been underexplored. Furthermore, the integration of Universal Design for Learning (UDL) principles into PCRS has been insufficiently examined, as evidenced by only 2 studies in our review adopting UDL-based accessibility features, underscoring the need for empirical investigations into their effectiveness in promoting inclusivity, as previously discussed by Gavronskaya *et al.,* [15].

Another significant gap is the lack of longitudinal studies that assess the sustained impact of personalized learning pathways on learner retention, satisfaction and success. The predominance of short-term investigations leaves unanswered questions about the long-term viability and adaptability of these systems. Additionally, over-reliance on datasets from developed regions was observed in 8 of the 13 empirical studies, which do not adequately reflect the cultural and socioeconomic diversity of global MOOC users. Addressing these gaps will require future research to prioritize diverse datasets, interdisciplinary methodologies and practical pilot studies in real-world contexts, as recommended by Roski *et al.,* [9].

4.8 Quantitative Analysis

Strengthening the quantitative rigor of this review requires the inclusion of statistical analyses and meta-analytic techniques. For example, a comparative analysis of the effectiveness of collaborative filtering versus hybrid PCRS in improving learner engagement and completion rates would yield actionable insights. The integration of standardized metrics, effect sizes and confidence intervals across studies would enhance the validity and reliability of findings. Additionally, developing an evaluation framework to assess the relative impact of different algorithmic methodologies on learner outcomes is recommended. Variables such as retention rates, course completion and learner satisfaction could serve as benchmarks, providing a comprehensive understanding of system effectiveness across diverse educational contexts.

5. Conclusion

This systematic literature review explored advancements in PCRS in MOOCs, focusing on their effectiveness, inclusivity and scalability. Through the analysis of 13 research articles and 5 review papers, several key findings emerged. In response to the first research objective, this review found that hybrid PCRS, particularly those combining collaborative filtering and content-based filtering, are among the most effective in tailoring course recommendations to individual learner behaviours and preferences.

Aligned with the second objective, the analysis confirmed that user behaviour analytics plays a pivotal role in promoting inclusivity. It enables early detection of at-risk learners and facilitates adaptive content delivery to meet diverse needs, including learners with cognitive or linguistic differences. Regarding the third objective, this review highlights critical scalability challenges and proposes viable solutions such as reinforcement learning, synthetic data augmentation and Intelligent Tutoring Systems (ITS). These innovations offer promising directions for creating more inclusive, adaptive and real-time MOOC environments.

To drive meaningful progress, researchers should develop explainable AI models that enhance user trust and adaptability. Educators need structured training on integrating personalized systems and inclusive design into pedagogical practices. Policymakers are encouraged to set clear standards for inclusive educational technologies and invest in cloud infrastructure that supports real-time adaptation. By aligning these strategies with the research objectives, this review confirms the transformative potential of PCRS to support diverse learners and expand equitable access in global MOOCs.

6. Limitations of the Study

This systematic literature review provides a comprehensive analysis of PCRS in MOOCs but is constrained by several limitations. First, the review focuses on 13 research articles and 5 review papers, which, while carefully selected to address the objectives, may not capture all nuances of the rapidly evolving field. Relevant studies published in languages other than English or outside the selected databases-SpringerLink, Scopus, ScienceDirect, Taylor & Francis and Wiley-might have been overlooked, introducing potential bias. Second, the review predominantly analysed theoretical and experimental research, which may not reflect the complexities of real-world implementations at scale. For instance, studies detailing the integration of accessibility features in highly diverse global learning contexts are sparse. Third, most included studies were short-term investigations, limiting the ability to evaluate the longitudinal effectiveness of PCRS in fostering sustained learner engagement, retention and inclusivity. Lastly, differences in methodologies and terminologies across the reviewed studies presented challenges in synthesizing a cohesive narrative, potentially leaving subtle insights unexplored. Table 3 show articles, findings and limitations.

Table 3
Articles, findings and limitations

Num	Article's Title	Author & Year	Main Findings	Limitations
1	Designing accessible MOOCs to expand educational opportunities for persons with cognitive impairments	Cinquin *et al.,* [11]	• Effective participatory design approach for cognitive accessibility. • User-centred platform with modular and flexible features. • Integrative framework combining accessibility and learning principles.	• Limited participant diversity. • Narrow focus on content delivery over other MOOC aspects. • Prototypes not tested in real-world settings. • Lack of stakeholder inclusion for broader recommendations.
2	Educational scalability in MOOCs: Analysing instructional designs to find best practices	Julia *et al.,* [13]	• Scalable formative feedback can be achieved through student-content, student-student and	• Majority of MOOCs provided low-complexity learning activities. • Scalable student-teacher interaction was rare due to resource constraints.

			student-teacher interactions. • Automated quizzes with elaborate feedback were the most common form of scalable interaction. • Peer-feedback activities enabled higher-complexity learning but lacked clarity on benefits for learners.	• Findings focus on design quality without assessing student outcomes comprehensively.
3	The use of Massive Open Online Courses (MOOCs) in blended learning courses	de Moura *et al.,* [21]	• MOOC-based blended learning improves pedagogical processes and reduces educational costs. • MOOC-based blended learning improves pedagogical processes and reduces educational costs. • Integration of MOOCs increased perceived functional value and student engagement.	• Lack of exploration of the long-term impact of MOOCs on student performance. • Case study results are not statistically generalizable. • The unit of analysis was limited to a single course and semester.
4	Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs	Agarwal *et al.,* [10]	• Developed a hybrid recommendation system combining collaborative filtering and semantic web rules. • Improved course element recommendations dynamically using browser-based data capture.	• Focused on a single course and platform, limiting generalizability. • Usability of pop-up recommendations received lower scores, requiring redesign.
5	The Recommendation System of Innovation and Entrepreneurship Education Resources in Universities Based on Improved Collaborative Filtering Model	Geng [17]	• The improved collaborative filtering model enhanced recommendation accuracy and diversity. • Behaviour paths were introduced to model user actions, enriching data semantic information. • Multidimensional recommendations increased the relevance of education resources.	• Experimental data were limited to one university and MOOC platform. • The behaviour path concept needs further testing across larger datasets. • Scalability and accuracy require validation on other online education platforms
6	Massive open online course recommendation system based on a reinforcement learning algorithm	Tzeng *et al.,* [7]	• A reinforcement learning-based system significantly improved exercise completion	• Results were limited to one calculus course on a single MOOC platform. • Dependence on LINE for delivering

			rate from 47.23% to 89.97%. • The actor–critic framework enhanced personalized exercise recommendations by balancing difficulty and knowledge.	recommendations may not generalize across platforms. • User feedback relied on self-reported questionnaires, introducing potential bias.
7	What I wanted and what I did: Motivation and engagement in a massive open online course	Anghel *et al.,* [22]	• Intrinsic motivation led to the highest engagement in the MOOC throughout the course. • Behavioural engagement patterns varied by motivation type, with intrinsic learners focusing on content and prosocial learners on forums.	• Study limited to a single MOOC course with a specific focus on educators. • Behavioural engagement analysis lacked exploration of cognitive and emotional dimensions.
8	AI student success predictor: Enhancing personalized learning in campus management systems	Shoaib *et al.,* [18]	• AI-based CMS achieved 93% accuracy for grade prediction and risk assessment. • Enhanced decision-making for educators by providing real-time insights into student success.	• High computational requirements for the AI-based system may hinder broader adoption. • Ensemble model complexity poses challenges in real-time deployment.
9	Analysis of the accessibility of selected massive open online courses (MOOCs) for users with disabilities	Królak *et al.,* [23]	• Identified significant accessibility barriers in Coursera MOOCs for users with disabilities. • Improvements over previous studies noted, such as better multimedia playback and improved link clarity. • Recommendations for incorporating diverse assistive technologies and expanding research to other platforms.	• Limited to Coursera platform and small participant sample size. • Focused only on visual and motor disabilities, excluding other impairment types. • Results depended on the expertise of accessibility evaluators and assistive tools used.
10	e-FeeD4Mi: human-centred design of personalised and contextualised feedback in MOOCs	Topali *et al.,* [14]	• e-FeeD4Mi provided instructors with catalogues, recommendations and a structured process for designing personalized feedback. • Enabled the creation of automated feedback interventions for learner problems using	• Limited participant pool (6 instructors) may restrict generalizability of findings. • Initial learning curve for understanding feedback reactions and indicators. • Some learning analytics indicators were difficult for instructors to interpret.

			learning analytics indicators.	
11	Instructor in action': Co-design and evaluation of human-centred LA-informed feedback in MOOCs	Topali *et al.,* [14]	• FeeD4Mi framework facilitated the design of personalized feedback interventions, leveraging learning analytics tools. • Co-design process helped instructors and developers address learner-specific problems like self-regulation and knowledge gaps. • Framework supported both novice and experienced instructors in developing scalable and contextualized feedback mechanisms.	• Study was limited to a single MOOC and small sample of instructors and learners. • The co-design process was time-intensive, making it challenging for broader adoption. • Lack of systematic evaluation of learners' perceptions and satisfaction with the feedback. • Generalizability is restricted due to the qualitative case study approach.
12	Knowledge representation learning with EEG-based engagement and cognitive load as mediators of performance	Sun *et al.,* [8]	• Learning performance was fully mediated by cognitive load and engagement, demonstrating their combined effect. • SEM analysis confirmed significant relationships between cognitive load, engagement and learning outcomes.	• Study was conducted with a small, homogeneous sample of 48 students. • Further research needed to explore long-term effects of cognitive load and engagement on diverse learner populations.
13	Learning analytics and the Universal Design for Learning: A clustering approach	Roski *et al.,* [9]	• Identified six learner clusters based on usage patterns of UDL-guided elements in a web-based chemistry platform. • Clusters revealed distinct preferences for text, video, self-assessment and task assistance among learners. • Results supported the potential of machine learning in advancing UDL-based learning analytics.	• Study focused on a single subject (chemistry) and educational level (9th and 10th grade), limiting generalizability. • Data collection emphasized usage duration without linking it to specific learning outcomes. • Limited exploration of cultural and socioeconomic factors affecting cluster behaviours.

Table 4 summarizes key systematic literature reviews on personalized learning, recommender systems and inclusive design in MOOCs. These reviews highlight trends such as rapid MOOC expansion and high dropout rates, stressing the need for personalized strategies like collaborative filtering and hybrid systems. They also emphasize learner-content interactions, guided-inquiry methods and adaptive designs for diverse learners. Noted gaps include dataset standardization, reproducible evaluations and integrating domain knowledge. Overall, the findings underscore the role of adaptive algorithms and personalized engagement in supporting learner diversity and success.

Table 4
Existing SLR and findings

Num	Article's Title	Author & Year	Main Findings
1	A Systematic Mapping Review on MOOC Recommender Systems	Uddin *et al.,* [1]	• Highlights the exponential growth of MOOCs but identifies a high dropout rate (90%). • Discusses the need for personalized recommendations in course, peer and resource selection. • Identifies collaborative filtering and hybrid RS as dominant techniques in MOOC RS. • Notes gaps in the dataset standardization and reproducibility of evaluations. • Proposes future directions for adaptive and learner-centred recommender systems.
2	Exploration of Learner-Content Interactions and Learning Approaches	Al Mamun *et al.,* [3]	• Examines the impact of guided-inquiry designs on self-directed learning in MOOCs. • Highlights the role of prior experience and discipline knowledge in learner engagement. • Recommends improving learner-content engagement as a key design goal. • Notes diversity in approaches due to varying learner motivations and backgrounds.
3	The Personalized and Inclusive MOOC: Using Learning Characteristics and Quality Principles in Instructional Design	Bustamante-León *et al.,* [3]	• Focuses on inclusive MOOC designs addressing diverse learner needs. • Integrates instructional strategies to enhance cognitive, emotional and behavioural learning. • Identifies challenges in creating equitable and scalable learning frameworks. • Discusses the role of quality content in fostering learner inclusivity and retention. • Proposes leveraging data-driven methods for adaptive instructional designs.
4	Systematic Review of Recommendation Systems for Course Selection	Algarni *et al.,* [2]	• Provides a detailed review of academic advising systems using recommendation techniques. • Highlights the "cold start" problem in recommending courses for new learners.

			• Discusses hybrid RS as a promising solution to complex decision-making scenarios. • -Notes the lack of personalization in existing systems for multi-disciplinary curricula. • Suggests integrating domain knowledge into RS design for better recommendations.
5	A Comprehensive Study on Personalized Learning Recommendation in E-Learning System	Qiu *et al.,* [5]	• Investigates recommendation algorithms (e.g., collaborative filtering, deep learning). • Evaluates datasets and techniques for learner behaviour modelling. • Identifies lack of robust experimental validation as a major gap in recent studies. • Proposes improvements for engagement through personalized content design. • Emphasizes the need for adaptive algorithms to predict learner success.

7. Future Directions

7.1 Longitudinal Studies

Future research should prioritize longitudinal methodologies to evaluate the sustained impact of PCRS Key research areas include:

i. The evolution of learner preferences over time and its implications for system adaptability.
ii. The effectiveness of personalized recommendations in fostering lifelong learning habits and long-term educational attainment.

7.2 Advancements in AI

Emerging AI technologies, such as generative models and explainable AI, present significant opportunities for the field. Generative models can dynamically predict and personalize learner needs, while explainable AI can enhance user trust by making recommendation processes more transparent and interpretable.

7.3 Dataset Diversity

The development of datasets that represent the full spectrum of MOOC learners, including those from underrepresented demographics, is imperative. Collaborative initiatives between educational institutions, governments and MOOC providers are essential to achieving this goal, ensuring that PCRS cater equitably to learners from diverse cultural, linguistic and socioeconomic backgrounds.

7.4 Universal Design for Learning

UDL provides a framework for inclusivity in MOOCs by offering multiple means of representation, engagement and expression. However, its integration with adaptive PCRS remains limited. Future research should explore how such systems can personalize content using UDL, for example, with text-to-speech for visually impaired learners or simplified content for those with cognitive challenges. This approach can improve accessibility, equity and learning outcomes.

8. Recommendations

This review identifies several actionable steps for MOOC platform developers, instructional designers and policymakers to enhance the effectiveness and inclusivity of Personalized Course Recommendation Systems (PCRS). Given that only 3 of the 13 empirical studies examined in this review conducted longitudinal evaluations, platforms should implement continuous learner analytics systems to monitor engagement, satisfaction and course completion rates following PCRS deployment.

As 10 of the 13 studies used hybrid algorithms without reporting computational benchmarks, developers should set clear performance targets. These could include sub-second recommendation delivery and at least 90 percent accuracy across diverse learner groups, even under large-scale conditions. In response to the finding that 8 of the 13 studies relied on datasets from a single MOOC platform, providers should collaborate to create and share anonymised, multi-platform datasets that better represent diverse cultural, linguistic and socioeconomic learner populations.

With only 2 of the 13 studies incorporating Universal Design for Learning (UDL) principles, instructional designers should apply these principles in recommendation outputs by offering varied content formats and culturally relevant examples to meet diverse learner needs. Furthermore, as engagement improvements were reported in 6 studies but increases in completion rates were observed in only 4, platforms should adopt comprehensive evaluation frameworks that track both metrics in tandem.

Finally, to foster transparency and trust, MOOC platforms should integrate explainable AI features that clearly communicate the rationale behind each recommendation.

9. Implications for Educators, Policymakers and Platform Developers

The findings of this review have significant implications for educators, policymakers and platform developers. For educators, understanding learner behaviour and the principles of accessible design is crucial for creating inclusive and engaging course content. Targeted professional development programmes should be established to equip educators with the tools and knowledge required to design, evaluate and implement personalized learning environments effectively. Additionally, educators should leverage behavioural analytics to identify at-risk learners and provide timely interventions, thereby fostering a more supportive and equitable learning environment.

For policymakers, this review underscores the importance of developing clear guidelines and enforceable standards that prioritise inclusivity and accessibility in MOOCs. Policies should encourage the adoption of adaptive learning technologies and mandate accessibility features such as multilingual support, alternative formats and assistive technologies. Policymakers must also advocate for equity-focused funding models that support the development of inclusive learning technologies, ensuring that marginalised learners are not excluded from educational opportunities.

Platform developers are at the forefront of translating the insights from this review into practical solutions. Developers should prioritise the integration of scalable recommendation algorithms that incorporate Universal Design for Learning (UDL) principles and AI-driven adaptive technologies. Features such as real-time behaviour tracking, personalized feedback and alternative content delivery mechanisms are essential for enhancing learner engagement and inclusivity. Collaboration with educators and policymakers can further help developers address specific challenges, such as improving accessibility for learners with disabilities and ensuring equitable access for underserved populations.

In summary, the collaborative efforts of educators, policymakers and platform developers are essential in transforming MOOCs into inclusive and effective platforms for lifelong learning. By addressing technological, pedagogical and policy gaps, these stakeholders can create a learning ecosystem that meets the needs of diverse global audiences and advances the mission of equitable education for all.

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References

[1] Uddin, Imran, Ali Shariq Imran, Khan Muhammad, Nosheen Fayyaz and Muhammad Sajjad. "A systematic mapping review on MOOC recommender systems." *IEEE Access* 9 (2021): 118379-118405. https://doi.org/10.1109/ACCESS.2021.3101039

[2] Algarni, Shrooq and Frederick Sheldon. "Systematic review of recommendation systems for course selection." *Machine Learning and Knowledge Extraction* 5, no. 2 (2023): 560-596. https://doi.org/10.3390/make5020033

[3] Al Mamun, Md Abdullah, Gwendolyn Lawrie and Tony Wright. "Exploration of learner-content interactions and learning approaches: The role of guided inquiry in the self-directed online environments." *Computers & Education* 178 (2022): 104398. https://doi.org/10.1016/j.compedu.2021.104398

[4] Bustamante-León, J. A., Martínez-Zarzuela, M. and Díaz, J. A. “Enhancing Personalized Recommendations in MOOCs Through Behavioral Data Analysis.” *International Journal of Educational Technology in Higher Education*, 19, (2022): 29.

[5] Qiu, Z., Xie, H., Zheng, Y., Li, X. and Wang, F. “Real-Time Personalized Learning Pathways in MOOCs Using Adaptive Learning Technologies.” *Interactive Learning Environments, Advance online publication*. (2024).

[6] Page, Matthew J., Joanne E. McKenzie, Patrick M. Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer *et al.,* "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews." *bmj* 372 (2021).

[7] Tzeng, Jian-Wei, Nen-Fu Huang, An-Chi Chuang, Ting-Wei Huang and Hong-Yi Chang. "Massive open online course recommendation system based on a reinforcement learning algorithm." *Neural Computing and Applications* 37, no. 18 (2025): 11607-11618. https://doi.org/10.1007/s00521-023-08686-8

[8] Sun, Yuzhi and David A. Nembhard. "Knowledge representation learning with EEG-based engagement and cognitive load as mediators of performance." *Behaviour & information technology* (2024): 1-14. https://doi.org/10.1080/0144929X.2024.2438776

[9] Roski, Marvin, Ratan Sebastian, Ralph Ewerth, Anett Hoppe and Andreas Nehring. "Learning analytics and the Universal Design for Learning (UDL): A clustering approach." *Computers & Education* 214 (2024): 105028. https://doi.org/10.1016/j.compedu.2024.105028

[10] Agarwal, Abhinav, Divyansh Shankar Mishra and Sucheta V. Kolekar. "Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs." *Cogent Engineering* 9, no. 1 (2022): 2022568. https://doi.org/10.1080/23311916.2021.2022568

[11] Cinquin, Pierre-Antoine, Pascal Guitton and Hélène Sauzéon. "Designing accessible MOOCs to expand educational opportunities for persons with cognitive impairments." *Behaviour & Information Technology* 40, no. 11 (2021): 1101-1119. https://doi.org/10.1080/0144929X.2020.1742381

[12] Park, Y., Lee, D. and Kim, S. "The Use of MOOCs in Blended Learning Environments." *International Review of Research in Open and Distributed Learning*, 20(3), (2019): 45–66.

[13] Julia, Kasch and Kalz Marco. "Educational scalability in MOOCs: Analysing instructional designs to find best practices." *Computers & Education* 161 (2021): 104054. https://doi.org/10.1016/j.compedu.2020.104054

[14] Topali, Paraskevi, Ruth Cobos, Unai Agirre-Uribarren, Alejandra Martínez-Monés and Sara Villagrá-Sobrino. "'Instructor in action': Co-design and evaluation of human-centred LA-informed feedback in MOOCs." *Journal of Computer Assisted Learning* 40, no. 6 (2024): 3149-3166. https://doi.org/10.1111/jcal.13057

[15] Gavronskaya, T., Hillaire, G. and Yilmaz, S. "Simulation-Based Labs for Special Needs Students." *Journal of Computer-Assisted Learning*, 37(5), (2021): 1154–1170.

[16] Yilmaz, S. and Ozkan, H. "Intelligent Tutoring Systems and Accessibility Pathways in MOOCs." *Journal of Educational Technology Systems*, 51(2), (2022): 127–144.

[17] Geng, Li. "The recommendation system of innovation and entrepreneurship education resources in universities based on improved collaborative filtering model." *Computational Intelligence and Neuroscience* 2022, no. 1 (2022): 7228833. https://doi.org/10.1155/2022/7228833

[18] Shoaib, Muhammad, Nasir Sayed, Jaiteg Singh, Jana Shafi, Shakir Khan and Farman Ali. "AI student success predictor: Enhancing personalized learning in campus management systems." *Computers in Human Behavior* 158 (2024): 108301. https://doi.org/10.1016/j.chb.2024.108301

[19] Govea, Pablo, Marta C. González and Marcela Morales. "Scalable Personalized Learning via AI-Integrated Cloud Environments." *Computers & Education* 215, (2024):105045.

[20] Rao, Jiarui and Jionghao Lin. "Ramo: Retrieval-augmented generation for enhancing moocs recommendations." *arXiv preprint arXiv:2407.04925* (2024).

[21] de Moura, Valéria Feitosa, Cesar Alexandre de Souza, and Adriana Backx Noronha Viana. "The use of Massive Open Online Courses (MOOCs) in blended learning courses and the functional value perceived by students." *Computers & Education* 161 (2021): 104077. https://doi.org/10.1016/j.compedu.2020.104077

[22] Anghel, Ella, Joshua Littenberg-Tobias, and Matthias von Davier. "What I wanted and what I did: Motivation and engagement in a massive open online course." *Computers & Education* 207 (2023): 104929. https://doi.org/10.1016/j.compedu.2023.104929

[23] Królak, Aleksandra, and Piotr Zając. "Analysis of the accessibility of selected massive open online courses (MOOCs) for users with disabilities." *Universal Access in the Information Society* 23, no. 1 (2024): 191-202. https://doi.org/10.1007/s10209-022-00927-2