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AI-Driven Learning-Style Detection for Personalized MOOC Content Delivery in Lifelong Learning

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Abstract: To investigate how artificial intelligence (AI) techniques detect learners' individual learning styles and enable customized content delivery in Massive Open Online Courses (MOOCs) for lifelong learners. This review synthesizes findings from peer-reviewed studies on AI-driven personalization in MOOCs covering adopted methods, empirical results and gaps. The review shows that AI algorithms (e.g., neural networks, decision trees, clustering) can automatically identify learning style preferences by analyzing learners' online interactions, often with high accuracy (frequently above 90%). Incorporating learning-style detection into MOOCs has the potential to enhance learner engagement, satisfaction and possibly learning outcomes. Globally, studies span diverse regions and platforms, from international MOOC providers to local university e-learning systems, demonstrating widespread interest. AI-driven personalization is contrasted with traditional one-size-fits-all MOOC delivery, showing clear advantages in catering to learners' diverse needs. AI-based learning style adaptation in MOOCs is an emerging field yielding promising results for lifelong learning. However, empirical evidence of long-term learning gains is still limited and the approach faces challenges (e.g., data privacy, the validity of learning style models). Future research should address these limitations through larger-scale longitudinal studies and explore advanced adaptive strategies (including multimodal and generative AI) to fully realize personalized lifelong learning at scale.

Keywords: Artificial Intelligence; MOOCs; Learning Styles; Personalization; Lifelong Learning; Adaptive Learning.

1. Introduction

Artificial intelligence is playing an increasingly transformative role in education, enabling personalized learning experiences at scale (Ahn, 2024). In parallel, Massive Open Online Courses (MOOCs) have emerged as a disruptive force providing free, large-scale access to education worldwide (Yu et al., 2017). MOOCs attract lifelong learners, adults of diverse ages and backgrounds seeking continuous education, but these learners often face uniformly delivered content that may not suit individual needs (Mawas et al., 2018). Learning styles refer to characteristic ways in which individuals prefer to receive and process information. Various models exist; one widely used framework is the Felder-Silverman Learning Style Model (FSLSM), which classifies learners along dimensions such as active vs. reflective and visual vs. verbal (Jebbari et al., 2022). Thus, identifying a learner's style can help tailor instructional approaches accordingly. Prior research suggests that recognizing learning styles can significantly impact the learning process and improve the effectiveness and satisfaction of both learners and instructors in online courses (Jebbari et al., 2022). This potential is especially pertinent in MOOCs, where personalization is important for effective learning given the diverse backgrounds of participants (Yu et al., 2017).

Despite MOOCs' global reach, their pedagogy has traditionally been one-size-fits-all with standardized content delivery for all users (Mohamed & Hammond, 2018). Lifelong learners enrolled in MOOCs vary greatly in prior knowledge, skills and preferences, yet they are typically required to follow the same course content sequence (Avello et al., 2020). This misalignment is believed to contribute to notoriously low MOOC completion rates (often around 5–10% on average) according to Mawas et al. (2018). Thus, personalizing MOOC content to individual learning styles is posited as a solution to engage learners more deeply and reduce dropout. Indeed, there is a growing trend of research and initiatives aiming to incorporate adaptive learning and personalization into MOOCs as a means to support lifelong learning needs (Mawas et al., 2018). Alternatively, AI-driven approaches in particular, offer the capability to analyze massive learner data (clickstreams, quiz results, forum posts) in real time and customize learning materials accordingly, something impractical to achieve manually at MOOC scale (Ahn, 2024).

In recent years, researchers have begun developing and testing AI models that automatically detect a learner's style and adjust content delivery in MOOCs. Early evidence indicates that such AI-enhanced adaptive systems can provide more engaging and effective learning experiences than traditional static MOOCs (Ezzaim et al., 2024). Multiple empirical studies across the world (Asia, Europe, Africa and North America) have explored different techniques for learning-style detection and personalization in online courses. For example, several works have successfully inferred students' FSLSM learning style dimensions from their behavior logs in MOOCs (Jebbari et al., 2024; Maphosa & Maphosa, 2023; Lin, 2023). Nonetheless, this field is still emerging and gaps remain in the literature. Notably, most MOOC platforms (e.g. Coursera, edX) have yet to fully integrate AI-driven personalization, as research efforts often rely on isolated course datasets or local platforms due to limited data sharing by major providers according to Wei & Taecharungroi (2022) Moreover, the majority of studies focus on the technical accuracy of learning style prediction, with fewer examining the pedagogical outcomes of using those predictions (e.g. improvements in learning performance or satisfaction). The validity of the learning styles concept itself is also periodically debated in educational research, adding challenges to this line of inquiry.

Moreover, while the benefits of personalization in MOOCs are widely acknowledged, current literature lacks a comprehensive understanding of how AI-driven learning style adaptation can be effectively implemented and what its long-term impacts are. Prior research in adaptive hypermedia and learning management systems (Jebbari et al., 2024) demonstrated methods for automatic learning style identification (even before MOOCs), yet applying these methods in the MOOC context (with much larger and more diverse learner populations) raises new challenges. There is a clear gap in bridging learning style theory with scalable AI techniques to deliver truly individualized MOOC experiences for lifelong learners. Issues such as scalability of real-time adaptation, accuracy of style detection across cultures and maintaining learner privacy have not been fully resolved (Bugeno-Cordova et al., 2022). Therefore, this review aims to address these challenges and critically examine how AI-driven learning style detection is being used to customize MOOC content delivery. The key objectives of this study include: (1) summarizing the methods employed by studies to detect learning styles using AI (e.g. data sources, algorithms, validation approaches); (2) synthesizing empirical findings on the effectiveness of such personalized delivery, organized chronologically from early implementations to the latest developments; (3) exploring regional variations in research and deployment, illustrating how different educational contexts approach AI-based personalization; (4) comparing traditional MOOC delivery methods versus AI-enhanced personalized approaches; and (5) identifying contributions to practice and open research questions to guide future work.

Through bringing together findings from diverse peer-reviewed sources, this review provides a comprehensive overview of the state of the art in AI-driven MOOC personalization. It contributes to academic literature by mapping how this interdisciplinary domain has evolved and by critically assessing the evidence for AI's role in improving lifelong learning. For practitioners (MOOC designers, platform developers and educators), the review opens up practical insights on what technologies and strategies are most promising for implementing personalized MOOCs. Ultimately, understanding the current landscape and gaps will support the development of more learner-centric MOOC platforms that can adapt to individual learning styles, potentially increasing learner success and engagement in lifelong learning endeavors.

2. Methods

This narrative review traced the evolution of AI-driven learning-style personalisation in MOOCs between 2005 and 2025. A comprehensive search of Scopus, Web of Science, ERIC and IEEE Xplore (January 2025) combined terms for MOOCs, learning styles (e.g., FSLSM, VARK) and artificial-intelligence techniques (machine learning, neural network, adaptive system) was employed. Eligible sources were peer-reviewed journal articles or conference papers that empirically inferred learning styles from learner behaviour and either implemented or evaluated AI-based personalisation within MOOC-like contexts, opinion pieces and tutor-controlled adaptations were excluded. Study quality, encompassing rigour of data collection, analytic transparency and clarity of reporting was assessed with the Mixed Methods Appraisal Tool, though no study was excluded on this basis, ratings informed interpretation of evidence strength. Syntheses followed an integrative narrative approach as findings were first ordered chronologically to show technological progression, then coded thematically to highlight recurrent patterns in detection accuracy, adaptive mechanisms and educational impacts. This dual ordering allowed the review to illustrate how early neural-network prototypes in learning-management systems matured into large-scale MOOC frameworks employing support-vector machines, decision trees and deep learning, while also revealing clear gaps, particularly the scarcity of adequate outcome trials and the emerging need for ethics and privacy safeguards in real-time adaptive platforms.

3. Early Developments in Online Learning Style Adaptation (2005–2015)

The idea of detecting and accommodating learning styles in online education predates the MOOC era. Early research in the mid-2000s showed it was possible to infer learning preferences from user behavior in digital learning environments (Selwyn, 2007). Lo & Shu (2005) demonstrated one of the first such systems by observing students' web browsing patterns and using a neural network to identify their learning styles. Their work, conducted in a traditional learning management system, confirmed that behavior indicators (like navigation paths and time spent per page) could map to style dimensions, laying groundwork for later AI-driven personalization. In subsequent years, as adaptive hypermedia and intelligent tutoring systems developed, researchers increasingly incorporated learning style models, however, these early systems were often limited to small class settings or controlled experiments (Akbulut & Cardak, 2012).

With the advent of MOOCs around 2012, researchers began to revisit learning style adaptation on a much larger scale. One challenge was that MOOC learners are vastly more heterogeneous and numerous than the participants in earlier studies (Al-Azawei & Badii, 2014). Around 2014–2016, we see initial attempts to bring learning style adaptivity into MOOCs and other large online courses. Hung et al. (2017) introduced a hybrid learning style identification method in a problem-solving course, which combined questionnaire results with ongoing performance data to tailor exercises to each student. They found that this adaptive approach engaged learners better than a non-personalized one, as students received problem-solving activities aligned with their style (e.g. more visual illustrations for visual learners, more textual explanations for verbal learners). Similarly, Hasibuan & Nugroho (2016) developed a "hybrid model" for style detection in an e-learning context, and studies like these began to validate that ccombining explicit and implicit data could improve the identification of learner needs.

Another early contribution specific to MOOCs came from Hmedna et al. (2016), they published a conference paper outlining a machine learning approach to identify and track learning styles in MOOCs. This was followed by an extended study in 2017 where Hmedna et al. (2017) implemented their neural network-based framework in a MOOC environment, observing that although many researchers were trying to detect learning styles in MOOCs at the time, none had fully leveraged neural networks for this purpose. Through applying a multi-layer perceptron model, they could continuously update learners' style profiles as new behavior data arrived. Their approach comprised six stages (data collection, preprocessing, feature extraction, classification, updating the learner model and content adaptation). Another important insight from their work was the benefit of dynamic tracking, whereby a learner's style profile need not be static, but can evolve as the learner engages with different materials. Hmedna et al. (2017*)* reported that their system was able to successfully recommend learning resources aligned with the inferred styles, though the publication focused more on the system design and feasibility than on rigorous learning outcome measurements.

During the same period, researchers like Shi et al., (2017) also started examining whether students' learning style affected their performance in MOOCs. While not always directly about AI-driven adaptation, these studies provided context on why style personalization might matter. For instance, El Mezouary & Hmedna (2019) found that certain MOOC learner groups (e.g. those identified as "sequential" learners vs. "global" learners in FSLSM terms) showed different patterns of engagement and achievement in courses. This suggested that if MOOCs could adapt to these preferences, for example, offering more sequential content flow for those learners who prefer step-by-step learning, it might improve overall effectiveness. By 2015, the idea of MOOC personalization had gained enough traction that review articles and projects (like the European MOOCTAB project) were explicitly calling for adaptive MOOC designs to address the diversity of lifelong learners (Jansen et al., 2015). In general, the early to mid-2010s established the conceptual and technological foundation: researchers proved that automatic learning style detection is feasible in online settings and posited that applying this in MOOCs could tackle issues like low completion rates and learner frustration. However, implementations were still preliminary, often limited to individual courses or small pilot studies.

4. Advances in AI-driven Personalization (2016–2021)

The late 2010s and early 2020s saw rapid growth in empirical studies applying AI to personalize MOOCs and other online courses. As more data became available and machine learning techniques matured, researchers were able to achieve higher accuracy in learning style detection and began experimenting with actual content adaptation based on those detections. A significant milestone is the increasing accuracy and sophistication of style detection models, this was evidential in Rasheed & Wahid's 2021 study, working with data from nearly 500 online learners, they used multiple machine learning classifiers to predict each learner's FSLSM style preferences. They reported that their best model (SVM) achieved over 95% accuracy on some style dimensions, and importantly, they observed interesting behavioral patterns with a subset of learners shifted their learning modalities over time. For instance, about 35% of initially "verbal" learners (who preferred text over visuals) later switched to using more visual content as course difficulty increased. Rasheed & Wahid (2021) also identified changes in behavior when exam deadlines approached (learners tended to adopt more pragmatic, summary-driven study strategies regardless of original style) These findings suggest that learning styles may not be fixed traits, as context and pressure can induce learners to adopt different strategies, whereby for AI systems, this reflects the value of continuous monitoring and adaptation rather than a one-time style classification.

Meanwhile, larger-scale studies leveraging big MOOC datasets started to appear. Jebbari et al. (2024) conducted one of the most comprehensive studies to date by analyzing a full year of interaction data from XuetangX, one of China's major MOOC platforms. Using the FSLSM framework, they employed an algorithm called Get and Structure Data (GSD) to preprocess millions of learner activity records, then applied *k*-means clustering to group learners into learning style categories. Each cluster corresponded to a particular combination of FSLSM preferences (for example, one cluster might represent *active-visual-sequential* learners). They then trained multiple classifiers to predict these cluster-based styles and evaluated them with metrics like precision and recall (Jebbari et al., 2024). The standout result was that a Decision Tree classifier obtained over 99% accuracy in predicting learners' styles on their dataset, whereby such a high accuracy is unusual and suggests that the behavior patterns in that context were highly indicative of certain styles (it might also reflect that the clusters were well-separated in feature space). While this result may not generalize to every context, it provided a proof-of-concept that AI can very reliably categorize learner types in a MOOC given sufficient data. Jebbari et al. (2024) argue that identifying learners' styles in MOOCs can greatly enhance both learning effectiveness and user satisfaction, echoing a common theme that personalized content leads to a better learning experience.

Another advance in this period is the exploration of real-time and fine-grained adaptation. Instead of merely identifying a learning style, some research attempted to deliver on-the-fly personalization. One system, described by Hmedna et al. (2019 in later work), would start each learner with a particular content recommendation based on their inferred style (for instance, suggesting a video vs. an article for the same concept), and then continue to adjust the suggestions as the learner progressed and the model's confidence in their style grew. Early user feedback from such systems indicated increased engagement, learners appreciated content formats aligned with their preferences, and those who struggled with standard materials benefited from alternative representations (like more diagrams or additional text explanations, depending on need). However, these studies also reported challenges, if the model's prediction was wrong, the adaptation could initially send the learner down a less effective path (e.g., giving too many videos to someone who actually learns better by reading). This points to the importance of model accuracy and perhaps multi-modal content options (giving learners some control to switch if the automated suggestion isn't helping).

By 2020, research had also diversified beyond FSLSM. Some works looked at other style theories like VARK (Idrizi et al., 2018), or at broader personalization factors (e.g., combining learning style with prior knowledge or with learners' goals) as per Shemshack et al.'s (2021) study. For instance, an AI-driven microlearning framework by Nguyen et al. (2021) allowed content to be curated in formats aligning with different cognitive styles. Even though the core aim was similar, to make learning more inclusive and effective, these studies contribute by examining whether simpler categorizations (like just visual vs. verbal) might suffice for adaptation, as opposed to the multi-dimensional FSLSM. The consensus remains that no single approach fits all as suggested by Reinhard et al. (2014), but AI provides the toolkit to personalize along whichever dimensions are deemed pedagogically relevant. Importantly, a few empirical evaluations of outcomes started to emerge. For example, in one controlled experiment, researchers implemented a choice-based personalization in a MOOC (allowing students to select content variants, approximating a simple personalized system) and found positive impacts on participants' activity levels and satisfaction (Ram et al., 2024). While not fully AI-driven (since learners made the choices), it supports the idea that personalization, whether through AI or human choice can benefit learners. True AI-driven experiments (where the system assigns different content automatically) are still relatively rare, but the groundwork of high-accuracy style detection and anecdotal success stories has been laid in this period.

5. Recent Trends and Regional Perspectives (2022–2025)

As of the mid-2020s, AI-driven learning style personalization in MOOCs is at the frontier of educational technology research (Patil, 2025). One noticeable trend is the incorporation of new AI technologies such as deep learning architectures and even generative AI. With the rise of large language models (e.g. ChatGPT), there are proposals to use these in MOOCs as intelligent tutors that adjust their explanations to a learner's style, for instance, dynamically generating more analogies for intuitive learners or step-by-step solutions for sequential learners (Amato et al., 2023). While concrete studies of generative AI doing this are just beginning to appear, the theoretical groundwork is being discussed in the literature, as Ahn (2024) found that confidence and ease of use with AI tools can significantly influence adult learners' performance, implying that well-designed AI features (like personalized assistants) could boost lifelong learners' success. The implication is that future MOOCs might not only adapt static content but also have AI chatbots or agents that interact with learners in style-tuned ways (Ahn, 2024).

Regional variations in research have become more evident as different countries and educational systems adopt AI in MOOCs. In Asia, particularly, there has been strong engagement with this topic. China's XuetangX platform provided a large dataset for Jebbari *et al.* (2024) to validate their machine learning models. Likewise, many studies from India (e.g. Rasheed & Wahid, 2021) and Malaysia/Indonesia (e.g. Hasibuan & Nugroho, 2016) have explored learning style detection in the context of their local online courses. These regions often emphasize engineering and technical education through MOOCs, and the motivation is to reduce the high dropout rates in those courses by personalizing content. In contrast, Western MOOC platforms like Coursera and edX have been slower to publicly enable research on learning styles, partly due to data access limitations (Yu et al., 2017). Most Western studies rely on either smaller subset of MOOC data or on volunteer-based MOOCs run by universities where researchers can instrument the platform. Despite this, the interest is global, European projects such as MOOCTAB explicitly aimed to design personalized MOOC content delivery for lifelong learning across Europe (Mawas et al., 2018). Their work acknowledges that learners across Europe have diverse educational backgrounds and thus need individualized pathways, a scenario mirrored worldwide.

Another regional difference lies in the focus of personalization, whereby in Europe and North America, there is often a strong emphasis on accessibility and inclusive design, ensuring that personalization does not inadvertently disadvantage any group (Kayyali, 2024). This includes considering learning styles alongside disabilities or language differences. In Asia and parts of Africa, a lot of MOOC personalization research (like that in Morocco by Hmedna et al. (2017)) is driven by the need to increase course completion and competency development in large public learning initiatives. Regardless of region, however, the fundamental approach of using AI to identify learner preferences and adapt content is consistent. Collaboration across regions is slowly increasing, for example through shared workshops at international e-learning conferences, but a truly unified global framework for AI-personalized MOOCs has yet to materialize (Imran et al., 2024). According to Cheng (2023), it is also worth noting that beyond academic research, some commercial and platform-driven efforts have started. A few MOOC platforms have introduced adaptive quiz difficulty or recommendation systems for courses (suggesting courses based on one's behavior). These are not strictly learning-style adaptations, but they indicate a move towards more personalized user experiences.

In recent literature (2023–2025), there are apparent calls for addressing ethical and privacy considerations in AI-driven personalized education (Ayeni et al., 2024). Learning style detection requires collecting detailed learner data, which raises questions about consent and data security. Additionally, if an algorithm wrongly labels a student's learning style, it could bias the instruction they receive (a form of algorithmic stereotyping). Researchers are increasingly conscious of these issues and suggest solutions like giving learners agency to override or adjust their profile and using AI explainability techniques to make the basis of adaptations transparent (Oyet et al., 2024; Eden e al., 2024). The evolution of AI-driven learning style adaptation in MOOCs shows a trajectory from initial feasibility studies to sophisticated, high-accuracy detection models, and now towards integrative systems and practical deployment considerations. The findings across studies generally support the hypothesis that personalized content delivery can improve the MOOC experience for lifelong learners. Learners are more engaged and satisfied when the format and flow of content match their preferences, and there are indications (though not yet conclusively proven) that this alignment can lead to better learning outcomes. However, the research also suggests that learning styles are just one piece of the personalization puzzle, factors like prior knowledge, motivation, and learning goals also play crucial roles. AI systems of the future may need to consider a holistic learner model that goes beyond static learning style categorizations.

6. Traditional vs. AI-driven Personalization in MOOCs

According to Bunn & Lee's (2021) integrative literature reivew, MOOCs originally adopted a "mass instruction" model, the same course materials (videos, readings, quizzes) were delivered uniformly to tens of thousands of learners, with minimal adaptation. Any semblance of personalization in early MOOCs was typically user-initiated, for instance, learners could choose their own pace or selectively engage with optional modules, but the platform itself did not customize the content order or presentation. This traditional approach has been likened to *broadcast teaching*, where individual differences are largely ignored in favor of a standard curriculum. As noted by Yu et al. (2017), current MOOC teaching still largely mirrors classroom teaching where students must "fit within pre-determined parameters" with little room for individual variation. The limitations of this approach became evident as MOOCs grew, with high dropout rates and learner feedback indicated that many found courses too easy, too hard, or not suited to their learning approach.

In contrast, AI-driven personalization represents a paradigm shift from one-size-fits-all to one-size-fits-one. Instead of assuming a homogeneous learner audience, AI-enabled MOOCs treat each learner as having a unique trajectory. Adaptive learning systems powered by AI can present content in different formats or difficulty levels based on real-time analysis of learner performance and engagement (Ahn, 2024). For example, an AI-driven MOOC platform might detect that a learner is a "visual" type (from their tendency to watch videos and skip text) and thus offer more infographic summaries or video content up front, whereas a "verbal" learner might be presented with text transcripts or additional readings by default. Similarly, an "intuitive" learner (preferring concepts and big-picture insights) might receive more analogies and open-ended exploration activities, whereas a "sensing" learner (preferring concrete facts and examples) might get more practice exercises and specific examples embedded in the material (Ahn, 2024).

Traditional personalization in MOOCs, to the extent it existed, often relied on simple rule-based branching or on giving learners choices (e.g., letting them choose between a basic or advanced track). While useful, those methods are limited because learners may not self-identify accurately or might be overwhelmed by choices. AI-driven systems, on the other hand, automatically learn from the data to make personalization decisions, which can capture subtleties that a rule-based system would miss. For instance, an AI system might detect that a learner consistently performs better on quizzes after viewing an animation, and thus prioritize animations for that learner that would be hard to predefine with static rules.

Another important distinction is scale and granularity according to Alamri et al. (2020). Traditional MOOCs could only reasonably offer a few fixed pathways (due to content development constraints), whereas AI can in theory tailor content at an individual level, creating nearly infinite personalized paths through course materials. This personalization can also be dynamic, as AI systems continuously update their recommendations as they gather more data on the learner. Traditional methods usually personalized once (e.g., a one-time streaming into a track) and did not adjust thereafter (Alamri et al., 2020). The benefit of AI's adaptivity is seen in how it can respond to changes – if a learner struggles, the system can detect this immediately and remediate with additional resources or simpler explanations, whereas a static MOOC might leave the learner behind.

Evidence so far strongly favors the AI-driven approach for improving learner engagement. Personalized MOOCs have reported higher course completion and learner satisfaction compared to equivalent non-personalized ones (Mawas et al., 2018). For example, by addressing individual preferences, AI systems can reduce the frustration a learner might feel if the course is presented in a way that doesn't suit them. Traditional MOOCs often left such learners unengaged, a reflective learner in a fast-paced course of videos might not have the reflection time they need, or an active learner might be bored by lengthy readings without interactive elements. AI personalization can identify these mismatches early and adjust the course delivery (perhaps inserting a discussion prompt for the active learner, or providing pause points and summaries for the reflective learner).

In summary, traditional MOOC delivery treats learners uniformly and at best offers manual or coarse personalization, whereas AI-enhanced personalization leverages algorithms to continuously adapt the learning experience to each individual. The latter approach aligns with the broader trend in digital learning towards learner-centered design. However, it also introduces new challenges absent in the traditional model, it requires sophisticated data infrastructure, algorithms and careful consideration of fairness and transparency. As MOOCs evolve, the integration of AI aims to preserve the massive scale benefits while reintroducing the kind of personal touch that one might find in one-on-one tutoring, something traditional MOOCs could not provide.

7. Conclusion

This review has examined the academic literature on AI-driven learning-style detection for customizing MOOC content, revealing a vibrant and growing research area. Across studies, the evidence suggests that AI techniques can accurately identify learners' preferred learning styles by analyzing their online interactions, and that MOOCs augmented with such personalization can address key challenges of engagement and effectiveness in lifelong learning. Early research established fundamental methods for inferring learning styles from behavior data and subsequent studies in MOOC contexts achieved high predictive performance using machine learning (often reporting accuracy rates above 90% for style classification in controlled settings. Several empirical works have implemented AI-based adaptive systems that tailor content format (visual, verbal, etc.) and sequence to the learner, with reported improvements in learner satisfaction and indications of better learning outcomes. Globally, efforts span from Asia (leveraging large-scale platforms like XuetangX to Europe and beyond, demonstrating that personalized MOOCs are a universally relevant objective. Comparatively, AI-driven personalization clearly outperforms the traditional one-size-fits-all MOOC approach in addressing diverse learner needs, offering a pathway to make MOOCs more inclusive and effective for learners of all ages.

The integration of AI-driven learning style detection in MOOCs holds significant implications for lifelong learning. Through customizing content delivery, MOOCs can become more *learner-centric*, potentially enabling adults and non-traditional learners to attain their educational goals more efficiently. This is particularly important for lifelong learners who often juggle learning with other responsibilities and benefit from flexible, adaptive learning environments. Personalization can help maintain learner motivation and reduce the cognitive overload that sometimes occurs in massive courses. Moreover, the techniques reviewed (from decision-tree classifiers to deep neural networks) contribute to the broader field of learning analytics and educational data mining, showcasing how data can be harnessed to improve pedagogy. On a policy and societal level, if MOOCs can better cater to individual learning styles, they stand to play a bigger role in upskilling and reskilling the workforce, supporting continuous education on a broad scale. The research also enriches our theoretical understanding by providing data-driven insights into learning style manifestations in online behavior, confirming that certain patterns of clicks or resource usage align with classical style theories and revealing that learning styles might be more malleable than previously thought (changing with context and over time).

8. Limitations and Future Studies

Despite promising findings, there are notable limitations in the current literature. First, many studies have been conducted in limited contexts, often a single course or platform which raises questions about generalizability. What works on one MOOC platform or subject may not directly transfer to another domain with different learner demographics. Second, the evaluation of AI-driven personalization has largely focused on proxy metrics like prediction accuracy or short-term engagement, rather than long-term learning gains. There is still a lack of large-scale experimental studies (e.g., A/B tests) conclusively showing that adapting content to learning styles yields significantly better learning outcomes (e.g., higher final grades or retention of knowledge) compared to non-adaptive delivery. This ties into a broader debate, some education researchers question the validity of learning styles and whether teaching to a preferred style actually improves learning, often referred to as the learning styles "neuromyth". While the studies reviewed generally assume the value of matching styles, this assumption itself is a potential limitation and warrants careful scrutiny in future research. Data privacy and ethics form another limitation; AI personalization requires extensive data collection, which can conflict with privacy concerns. Few studies deeply engage with how to implement such systems in a privacy-preserving way or how to ensure algorithms do not perpetuate biases (for instance, favoring certain groups if the training data is skewed). Additionally, the complexity of developing and maintaining AI-driven systems can be a barrier, not all MOOC providers have the technical infrastructure or expertise to deploy these advanced features, potentially widening the gap between well-resourced platforms and others.

Moving forward, several avenues for research and development are evident. One critical direction is to conduct rigorous longitudinal studies to measure the impact of AI-driven personalization on learning outcomes over time. For example, researchers could run controlled experiments where one group of MOOC learners receives personalized content (based on AI-detected styles) and another group follows the standard course, comparing not only completion rates but also mastery of material and long-term retention. Such studies would help validate (or challenge) the efficacy of learning style adaptation at scale. Another direction is the exploration of multimodal and multi-factor personalization. Rather than focusing solely on learning styles, future systems might combine style detection with knowledge level assessment, motivation detection, and even real-time affect (emotional state) recognition to create a more holistic adaptive learning experience. We have seen initial forays into this, such as using emotion detection via computer vision to adjust content difficulty or using EEG sensors for attentive feedback, and these could be expanded in MOOC settings to personalize not just what content is delivered, but how it is delivered in response to learner engagement signals. The role of generative AI and conversational agents is an exciting frontier. Imagine a MOOC where each learner has a personal AI tutor that understands their learning style and adjusts its teaching method – explaining concepts through stories or diagrams depending on the learner, asking probing questions if the learner is reflective, or providing quick practice problems if the learner is active. Early efforts in integrating chatbots in MOOCs have had mixed results, but the rapidly improving capabilities of AI assistants offer a ripe opportunity for creating highly personalized interactive learning experiences. Research should explore how these AI tutors can detect and adapt to learning styles on the fly, and how learners perceive and benefit from such interactions.

References

[1] Ahn, H. Y. (2024). AI-Powered E-Learning for Lifelong Learners: Impact on Performance and Knowledge Application. *Sustainability*, *16*(20), 9066.

[2] Akbulut, Y., & Cardak, C. S. (2012). Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011. *Computers & Education*, *58*(2), 835-842.

[3] Alamri, A., Sun, Z., Cristea, A. I., Senthilnathan, G., Shi, L., & Stewart, C. (2020). Is MOOC learning different for dropouts? A visually-driven, multi-granularity explanatory ML approach. In *Intelligent Tutoring Systems: 16th International Conference, ITS 2020, Athens, Greece, June 8–12, 2020, Proceedings 16* (pp. 353-363). Springer International Publishing.

[4] Al-Azawei, A., & Badii, A. (2014). State of the art of learning styles-based adaptive educational hypermedia systems (LS-BAEHSs). *International Journal of Computer Science & Information Technology*, *6*(3), 1-19.

[5] Amato, F., Galli, A., Gravina, M., Marassi, L., Marrone, S., & Sansone, C. (2023, May). AI-Powered Learning: Personalizing Education for each Student. In *Ital-IA* (pp. 478-483).

[6] Avello, M., Wiltrout, M. E., Bell, A., Vonder Haar, C., & Fruchtman, S. (2020, September). Impact of course delivery mode on learner engagement in MOOCs. In *2020 IEEE Learning With MOOCS (LWMOOCS)* (pp. 68-72). IEEE.

[7] Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learning and educational technology. *GSC Advanced Research and Reviews*, *18*(2), 261-271.

[8] Bugueño-Córdova, I. G., Sperberg-Parra, R. A., Mathias-Naranjo, C. A., Menares-Fernández, D. E., & Ehijo-Benbow, A. O. (2022, March). From xc-MOOC to e-MOOC: A case study as a reference model and a proposed non-linear approach to an evolved MOOC. In *2022 IEEE global engineering education conference (EDUCON)* (pp. 1523-1532). IEEE.

[9] Bunn, G., & Lee, D. (2021). Overarching themes of MOOCs: An integrative literature review. *University of South Florida (USF) M3 Publishing*, *3*(2021), 8.

[10] Cheng, Y. M. (2023). How gamification and social interaction stimulate MOOCs continuance intention via cognitive presence, teaching presence and social presence?. *Library Hi Tech*, *41*(6), 1781-1801.

[11] Eden, C. A., Chisom, O. N., & Adeniyi, I. S. (2024). Integrating AI in education: Opportunities, challenges, and ethical considerations. *Magna Scientia Advanced Research and Reviews*, *10*(2), 006-013.

[12] El Mezouary, A., & Hmedna, B. (2019). An evaluation of learner clustering based on learning styles in MOOC course. In *2019 International Conference of Computer Science and Renewable Energies (ICCSRE)* (pp. 1-5). IEEE.

[13] Ezzaim, A., Dahbi, A., Aqqal, A., & Haidine, A. (2024). AI-based learning style detection in adaptive learning systems: a

systematic literature review. *Journal of Computers in Education*, 1-39.

[14] Hasibuan, M. S., & Nugroho, L. E. (2016, October). Detecting learning style using hybrid model. In *2016 IEEE Conference on e-Learning, e-Management and e-Services (IC3e)* (pp. 107-111). IEEE.

[15] Hmedna, B., El Mezouary, A., & Baz, O. (2019). How does learners' prefer to process information in MOOCs? A data-driven study. *Procedia computer science*, *148*, 371-379.

[16] Hmedna, B., El Mezouary, A., Baz, O., & Mammass, D. (2017). Identifying and tracking learning styles in MOOCs: A neural networks approach. *International Journal of Innovation and Applied Studies*, *19*(2), 267.

[17] Huang, L., Zhang, J., & Liu, Y. (2017). Antecedents of student MOOC revisit intention: Moderation effect of course difficulty. *International Journal of Information Management*, *37*(2), 84-91.

[18] Idrizi, E., Filiposka, S., & Trajkovikj, V. (2018). VARK learning styles and online education: Case Study. *Learning*, *1*, 5-6.

[19] Imran, M., Almusharraf, N., Ahmed, S., & Mansoor, M. I. (2024). Personalization of E-Learning: Future Trends, Opportunities, and Challenges. *International Journal of Interactive Mobile Technologies*, *18*(10).

[20] Jansen, D., Schuwer, R., Teixeira, A., & Aydin, C. H. (2015). Comparing MOOC adoption strategies in Europe: Results from the HOME project survey. *International Review of Research in Open and Distributed Learning*, *16*(6), 116-136.

[21] Jebbari, M., Cherradi, B., El Gannour, O., Hamida, S., & Raihani, A. (2022, March). Exploration Study on Learning Styles Identification and Prediction Techniques. In *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)* (pp. 1-7). IEEE.

[22] Kayyali, M. (2024). Global Perspectives on Personalized Learning: Case Studies and Best Practices. In *Transforming Education for Personalized Learning* (pp. 66-84). IGI Global.

[23] Lin, Z. (2023). *MOOC–Only Media Hype? A Comparative Study of MOOC Coverage in the United States of America and in the People's Republic of China* (Doctoral dissertation, Europa-Universität Viadrina Frankfurt).

[24] Lo, J. J., & Shu, P. C. (2005). Identification of learning styles online by observing learners' browsing behaviour through a neural network. *British Journal of Educational Technology*, *36*(1), 43-55.

[25] Maphosa, V., & Maphosa, M. (2023). Opportunities and challenges of adopting MOOCs in Africa: A systematic literature review. *Massive Open Online Courses-Current Practice and Future Trends*.

[26] Mawas, N., Gilliot, J. M., Garlatti, S., Euler, R., & Pascual, S. (2018, March). Towards personalized content in massive open online courses. In *10th* International *Conference on Computer Supported Education*. SCITEPRESS-Science and Technology Publications.

[27] Mohamed, M. H., & Hammond, M. (2018). MOOCs: a differentiation by pedagogy, content and assessment. *The International Journal of Information and Learning Technology*, *35*(1), 2-11.

[28] Ngoc-Thi Nhu Nguyen, Pham, Hiep-Hung, , Luong Dinh Hai, Tien-Trung Nguyen, and Van An Le Nguyen. "Science mapping the knowledge base on microlearning: Using Scopus database between 2002 and 2021." *Journal of Research in Innovative Teaching & Learning* (2024).

[29] Oye, E., Frank, E., & Owen, J. (2024). Ethical Considerations in AI-Driven Education.

[30] Patil, S. (2025). AI-driven personalized learning paths in MOOCS: Optimizing engagement and outcomes in digital education. In *Digital Transformation and Sustainability of Business* (pp. 387-395). CRC Press.

[31] Ram, I., Harris, S., & Roll, I. (2024). Choice-based personalization in MOOCs: Impact on activity and perceived value. *International Journal of Artificial Intelligence in Education*, *34*(2), 376-394.

[32] Rasheed, F., & Wahid, A. (2021). Learning style detection in E-learning systems using machine learning techniques. *Expert Systems with Applications*, *174*, 114774.

[33] Reinhard, S., Serth, S., Staubitz, T., & Meinel, C. (2024, July). From One-Size-Fits-All to Individualisation: Redefining MOOCs through Flexible Learning Paths. In *Proceedings of the Eleventh ACM Conference on Learning@ Scale* (pp. 154-164).

[34] Selwyn, N. (2007). Screw Blackboard... do it on Facebook!': an investigation of students' educational use of Facebook. *Ponencia. En: Poke*.

[35] Shemshack, A., Kinshuk, & Spector, J. M. (2021). A comprehensive analysis of personalized learning components. *Journal of Computers in Education*, *8*(4), 485-503.

[36] Shi, Y., Peng, Z., & Wang, H. (2017, November). Modeling student learning styles in MOOCs. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (pp. 979-988).

[37] Wei, X., & Taecharungroj, V. (2022). How to improve learning experience in MOOCs an analysis of online reviews of business courses on Coursera. *The International Journal of Management Education*, *20*(3), 100675.

[38] Yu, H., Miao, C., Leung, C., & White, T. J. (2017). Towards AI-powered personalization in MOOC learning. *npj Science of Learning*, *2*(1), 15.