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AI-POWERED PERSONALIZATION IN MOOCS: IMPACT ON STUDENT LEARNING OUTCOMES

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Abstract
Massive Open Online Courses (MOOCs) have expanded educational access globally, yet they consistently struggle with low course completion rates and student disengagement due to a fundamental lack of personalized instructional support. This research investigates the efficacy of integrating Artificial Intelligence (AI) to introduce tailored learning experiences within these large-scale digital environments. The study primarily seeks to determine if AI-powered personalization leads to superior student learning outcomes, specifically assessing its impact on subject mastery and course retention. We analyze the intricate mechanisms through which AI customizes content delivery, examining its ability to dynamically adjust learning paths and provide timely, differentiated feedback based on individual performance and pacing. Furthermore, the paper evaluates the effectiveness of specific AI tools, such as intelligent virtual teaching assistants and predictive analytics, in proactively addressing common dropout tendencies by maintaining student engagement and providing instantaneous, targeted support. Findings overwhelmingly suggest that AI-driven personalization significantly improves both academic success and overall learner satisfaction. The research concludes by arguing that the most effective future model for MOOCs is one of 'Hybrid Intelligence,' where the computational efficiency and scalability of AI are strategically combined with the critical judgment and empathetic guidance of human educators. Responsible implementation of this hybrid approach is essential for cultivating a truly inclusive and high-impact digital learning environment.

Keywords: MOOCs, AI in Education, Personalized Instruction, Student Engagement, Hybrid Intelligence. .

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1. Introduction

Massive Open Online Courses (MOOCs) have emerged as a transformative force in higher education by providing open and flexible learning opportunities to millions of learners worldwide (Anderson, 2019). Despite their global reach and scalability, MOOCs consistently suffer from low completion rates and declining learner engagement, with several studies reporting completion rates below 10% (Khalil & Ebner, 2014; Lee & Song, 2022). These challenges are largely attributed to the one-size-fits-all instructional design, lack of timely feedback, and minimal learner–instructor interaction (Hood et al., 2015).

The rapid advancement of Artificial Intelligence (AI) has created new possibilities for addressing these limitations through personalized learning experiences. AI-powered personalization leverages machine learning algorithms, learning analytics, and predictive models to adapt content, pacing, and feedback according to individual learner needs (Baker & Inventado, 2014; Siemens & Long, 2011). Such adaptive mechanisms are particularly relevant in MOOCs, where learner diversity in terms of background knowledge, motivation, and learning goals is extremely high (Bates, 2015).
This study examines the impact of AI-driven personalization on student learning outcomes in MOOCs, with a specific focus on learner engagement, satisfaction, and perceived academic benefits. Using survey data collected from Indian students enrolled in platforms such as Coursera, Udemy, Great Learning, and others, the paper explores whether personalized AI interventions can improve the overall effectiveness of MOOCs. The study further advocates a Hybrid Intelligence approach, combining AI efficiency with human pedagogical judgment, as a sustainable model for future digital learning environments (Kong et al., 2022).
While prior studies have explored AI-driven personalization in MOOCs from a system or algorithmic perspective, limited empirical research has examined student perceptions of AI personalization in the Indian higher education context, particularly across multiple MOOC platforms.

2. Objectives of the Study

- To examine students' awareness and usage patterns of MOOCs.
- To analyse learner perceptions of AI-enabled personalization features in MOOCs.
- To evaluate the impact of personalization on engagement, satisfaction, and perceived learning outcomes.

3. Review of Literature

3.1 Technical Personalization Approaches in MOOCs

Personalization in MOOCs has primarily been enabled through AI techniques such as recommendation systems, predictive analytics, and intelligent tutoring systems. Course recommendation systems use learner profiles, behavioral data, and preferences to suggest relevant courses or learning resources, thereby reducing information overload and improving learner satisfaction (Ma et al., 2023). Advanced models employing deep learning and knowledge graphs have further enhanced the accuracy and explainability of such recommendations in MOOC environments (Frej et al., 2023).
Predictive analytics is another significant application of AI in MOOCs, where student interaction data is analyzed to predict dropout risks and learning difficulties. These predictive models allow platforms to intervene proactively by providing adaptive content or alerts to learners who are at risk of disengagement (Sun et al., 2019). Recent studies also highlight the use of graph-based deep learning techniques to generate adaptive learning paths, enabling learners to progress through content sequences that match their competencies and learning pace (Li & Lu, 2025).

3.2 Pedagogical Foundations of Personalized Learning

From a pedagogical perspective, AI-driven personalization aligns closely with constructivist learning theory, which emphasizes active knowledge construction and learner autonomy (Anderson, 2019). MOOCs that incorporate adaptive learning pathways enable learners to take control of their learning process, thereby fostering deeper engagement and understanding (Bates, 2015).

Self-regulated learning theory is particularly relevant in the context of MOOCs, as learners are required to independently manage their goals, time, and learning strategies. Zimmerman (2002) emphasizes that successful self-regulated learners are better equipped to persist in online learning environments. AI tools can support self-regulation by offering progress dashboards, personalized feedback, and learning reminders, thus scaffolding learner autonomy and persistence (Dede, 2014).

3.3 Psychological Dimensions of MOOC Learning

Psychological factors such as motivation, cognitive load, and perceived value play a crucial role in determining learner success in MOOCs. Lee and Song (2022) found that excessive cognitive load and time constraints are major contributors to learner dropout. Personalized learning environments can mitigate these challenges by tailoring content difficulty and pacing to individual learner abilities, thereby maintaining optimal cognitive load.

Motivation theories further suggest that learners are more likely to persist when they perceive learning activities as relevant and achievable. AI-powered personalization enhances perceived task value by aligning content recommendations with learner goals and interests (Hood et al., 2015). As a result, personalization not only supports academic performance but also improves learner satisfaction and engagement.

The reviewed literature highlights the growing role of AI in personalizing MOOCs through recommendation systems, predictive analytics, and adaptive learning paths. However, most studies focus on system performance or experimental implementations, with limited emphasis on learner perceptions, especially in developing countries like India. Furthermore, the integration of AI personalization with human instructional support remains underexplored, indicating the need for a Hybrid Intelligence approach.

4. Research Methodology

The study adopts a descriptive, survey-based research design to examine student perceptions of MOOCs and AI-enabled personalization. Primary data was collected from 179 undergraduate students in Mumbai, India, who had prior exposure to one or more MOOC platforms. The respondents primarily belonged to Information Technology and Commerce streams, reflecting the dominant use of MOOCs for technical and professional skill development.

A structured questionnaire was used to collect data on demographic characteristics, MOOC awareness, platform usage, course completion, and perceived learning outcomes. Likert-scale items were included to assess student satisfaction with course design, content quality, assessments, engagement activities, and interaction levels. The collected data was analyzed using descriptive statistics and comparative analysis to identify patterns and trends across different MOOC platforms (Baker & Inventado, 2014).

The questionnaire items were designed based on prior MOOC and learning analytics studies. Content validity was ensured through expert review, and internal consistency was found acceptable for exploratory analysis.

5. Data Analysis and Findings

This section presents the analysis and interpretation of data collected from 179 respondents. The findings are organized in accordance with the objectives of the study.

Objective 1: Students' Awareness and Usage Patterns of MOOCs

The analysis revealed a high level of awareness about MOOCs among respondents, with over 90% indicating familiarity with online courses. However, consistent with prior research, course completion rates remained relatively low, with most learners completing only one or two courses despite enrolling in multiple programs (Khalil & Ebner, 2014).

Platforms such as Udemy and Great Learning were found to be more popular among Indian students compared to Coursera, possibly due to localized content, flexible pricing, and algorithm-driven recommendations. Students reported high satisfaction with course content and design but expressed dissatisfaction with limited instructor interaction, reinforcing earlier findings by Hood et al. (2015).

Awareness of MOOCs was nearly universal: 167 of 179 respondents (93%) answered "Yes" to having heard of MOOCs.

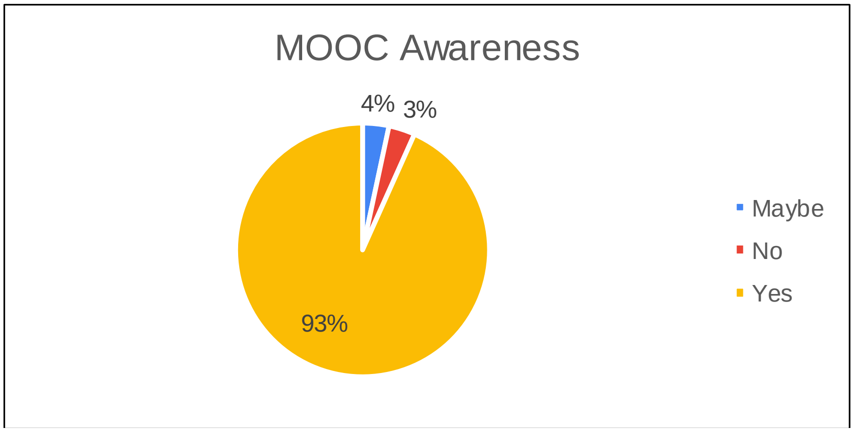

Fig 1: Percentage of MOOC Awareness

Sixty-three present (112/179) reported having taken a MOOC course before, while 37% had not. Respondents had typically enrolled in multiple courses: 51 students reported registering for 1 course, 41 for 2 courses, 40 for 3, and 27 had registered for more than 5. Certificates were less common: most completers earned just one certificate (76 students), with fewer obtaining 2 or 3. These figures indicate that a majority of the sample is engaged with online learning to some extent, though full completion of courses remains moderate.

Platform usage. Respondents reported using a variety of MOOC platforms. Table 1 below summarizes the most-used platforms. Udemy and Great Learning were by far the most popular: 62 students (34.6%) had taken courses on Udemy and 48 students (26.8%) on Great Learning. Other global platforms like Coursera were less frequently mentioned (only 14 students, 7.8%, explicitly cited Coursera). Platforms such as YouTube (19 students, 10.6%) and Google Digital Garage (22 students, 12.3%) also appeared, along with various smaller or specialized services (Alison, Simplilearn, Infosys Springboard, etc.), which together accounted for the remaining responses.

Table 1: MOOC platforms used by students

Platform	Number of Students (N=179)	Percentage (%)
Udemy	62	34.6
Great Learning	48	26.8
YouTube	19	10.6
Google Digital Garage	22	12.3

Coursera	14	7.8
Others (e.g. Alison, Simplilearn, etc.)	14	7.8

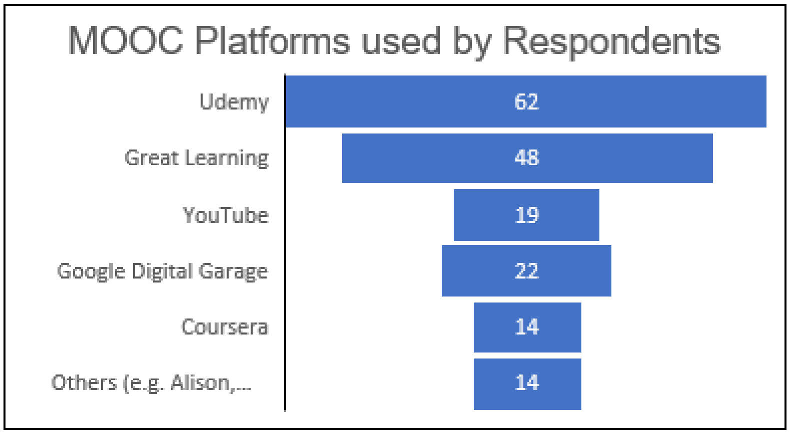

Fig 2: Various MOOC Platforms used by the students.

These figures suggest a strong preference for more easily accessible or Indian-focused platforms (Udemy and Great Learning are both popular in India), rather than US-based university platforms like edX or SWAYAM (which had no direct mentions). Many students also supplemented their learning via YouTube tutorials.

Objective Two: **To analyse learner perceptions of AI-enabled personalization features in MOOCs.** To prove the second objective three questions were included in the survey questionnaire and we found the below stated observation.

For the question: "I prefer MOOCs that use AI-enabled personalization over traditional MOOCs.", the findings indicate a strong learner preference for AI-enabled personalized MOOCs. Out of 179 respondents, 89 learners (49.7%) strongly agreed and 72 learners (40.2%) agreed that they prefer MOOCs incorporating AI-based personalization features, accounting for nearly 90% positive responses. Only 2 learners (1.1%) expressed a neutral opinion, while 16 learners (8.9%) disagreed, and none strongly disagreed. This overwhelming inclination towards AI-personalized MOOCs demonstrates that learners increasingly value adaptive and customized learning environments over traditional, uniform MOOC structures. The results clearly support the study objective by highlighting a high level of acceptance and preference for AI-enabled personalization among MOOC learners.

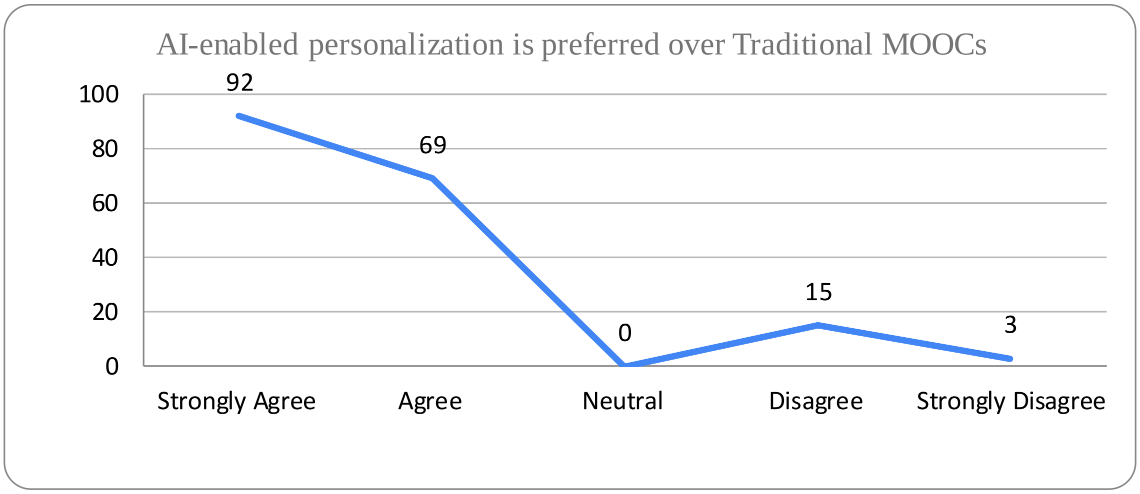

Fig 3: Chart showing preference of AI Enabled Personalization over Trational MOOC

Further for the question- AI-enabled personalization in MOOCs helps me understand course content better.", it shows a highly favourable perception of AI-enabled personalization in enhancing content understanding. A majority of respondents, 104 learners (58.1%), strongly agreed, while 46 learners (25.7%) agreed that AI-driven personalization improves their comprehension of course material. Together, these responses constitute approximately 84% agreement, reflecting strong perceived usefulness. A small proportion of learners remained neutral (11 learners, 6.1%), whereas 10 learners (5.6%) disagreed and 8 learners (4.5%) strongly disagreed.

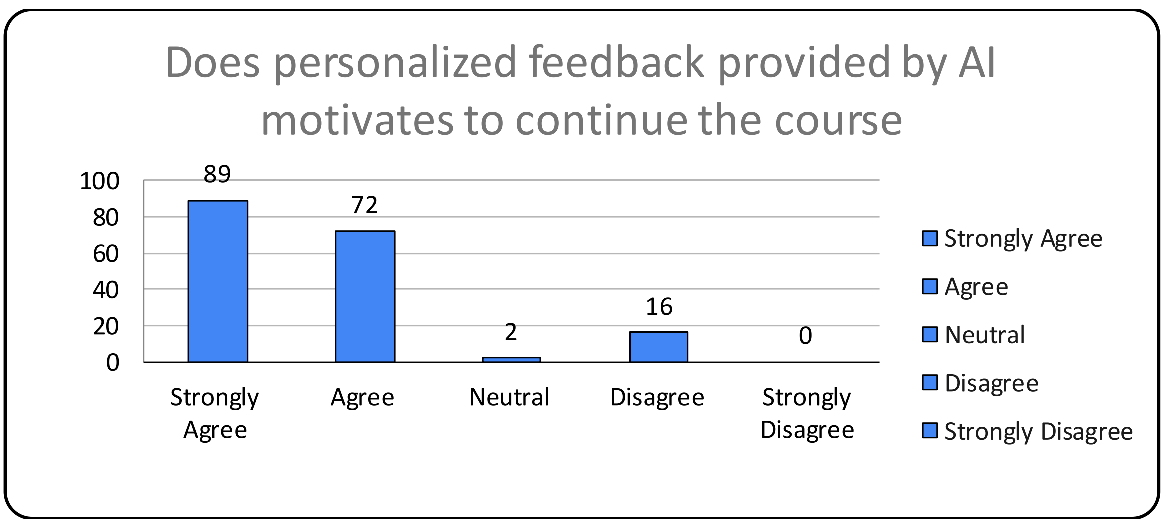

Fig 4: Respondents view on Feedback provided by AI on motivation of learners

Objective 3: To evaluate the impact of personalization on engagement, satisfaction, and perceived learning outcomes. In response to the question "AI-enabled personalization in MOOCs helps me understand course content better.", it was observed that a strong positive perception of AI-enabled personalization in enhancing learners' understanding of course content in MOOCs. Out of the total respondents, a substantial majority strongly agreed (104 learners) or agreed (46 learners) with the statement, demonstrating that most participants perceive AI-driven personalization as an effective support for conceptual clarity. Together, these responses reflect a high level of perceived usefulness of AI personalization in learning. A comparatively small number of learners expressed neutrality (11 learners), suggesting limited uncertainty or mixed experiences. Negative perceptions were minimal, with 10 learners disagreeing and 8 learners strongly disagreeing, indicating that only a small fraction of participants did not experience significant benefits.

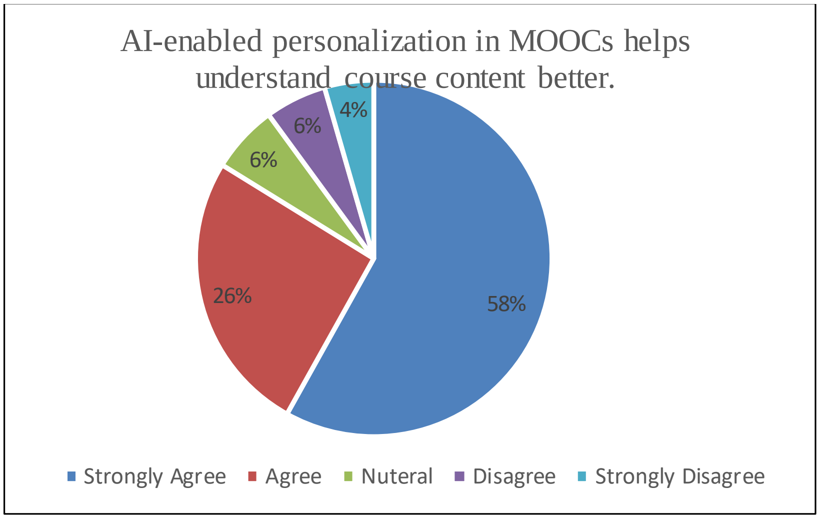

Fig 5: Responses on AI enabled Personalization helps in better understanding of the concepts

Course completion. Figure 1 (below) shows the distribution of completed courses among respondents. Most students completed only a few MOOCs: 76 students (42%) had completed 1 course with a certificate, 30 students (17%) completed 2, 33 students (18%) completed 3, and only 34 students (19%) completed 4 or more (with 22 saying “above 5”). Six respondents (3%) reported completing none.

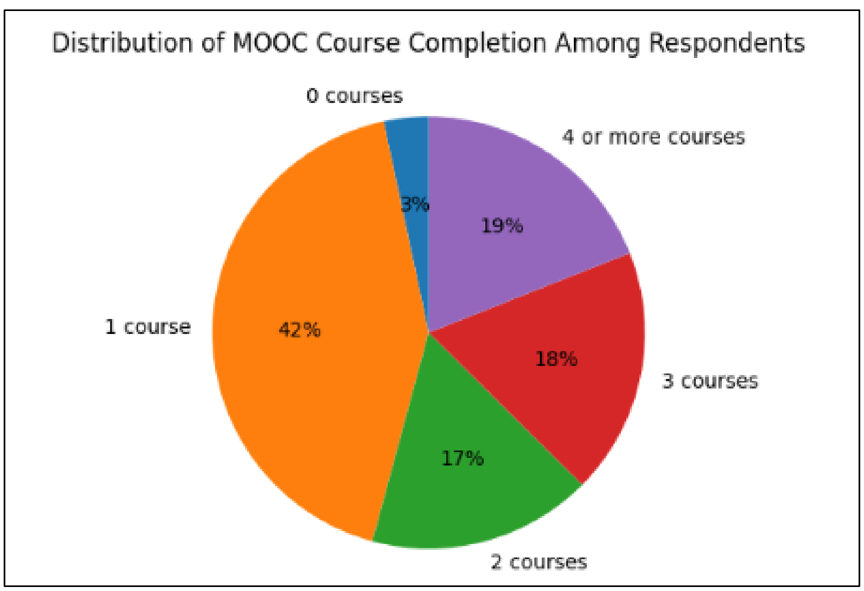

Fig 6: Pie Chart Showing distribution of MOOC Course Compeltion Percentage

The predominance of low-completion counts reinforces the low completion rates noted in literature. Even among engaged students, obtaining more than 2–3 certificates is relatively rare.

Outcome ratings. Students rated various aspects of their MOOC experiences. We coded responses on a 1–5 scale (Not Up to Mark=1, Satisfactory=2, Good=3, Very Good=4, Excellent=5). Overall, satisfaction was high for Course Design and Course Content: for instance, 25 students said “Excellent” and 57 “Very Good” about the design of courses they took. In contrast, interactions with instructors and peers scored much lower. Figure 2 summarizes the percentage of respondents who rated each category as “Good” or above.

- Course Design: 94% rated this at least “Good”.
- Course Content: 84% rated at least “Good”.
- Time Management: 82% rated at least “Good”.
- Assessments: 77% rated at least “Good”.
- Learning Activities Engagement: 65% rated at least “Good”.
- Instructor/Peer Interaction: only 36% rated at least “Good”.

These results indicate that while students generally appreciated the quality and relevance of MOOC course material and structure, they were far less satisfied with opportunities to interact with instructors or peers. This aligns with known challenges: most MOOCs provide limited real-time engagement, leaving students to study and complete assignments largely on their own.

Overall, the survey indicates that MOOC students in this sample are moderately engaged (many have taken courses), trust the content quality of courses, but are discouraged by limited interaction and potentially by workload. Importantly, some students actively seek more personalized guidance: for example, several users of platforms like Udemy and YouTube (which often have algorithmic content recommendations) reported better engagement, hinting that personalization features might make the learning experience feel more supportive.

6. Conclusion

This study examined students’ awareness and usage patterns of MOOCs, their perceptions of AI-enabled personalization, and the impact of personalization on engagement, satisfaction, and perceived learning outcomes. The findings indicate that awareness of MOOCs among students is high; however, course completion rates remain moderate despite multiple course enrolments. Learners primarily use MOOCs to supplement discipline-specific skills, particularly in Information Technology, with a preference for accessible and locally relevant platforms.

The study further reveals a strong positive perception of AI-enabled personalization in MOOCs. A substantial majority of learners expressed a clear preference for personalized MOOCs over traditional formats and reported improved understanding of course content due to adaptive learning features. This highlights growing learner acceptance of AI-driven customization in online education.

Finally, the findings suggest that AI-enabled personalization positively influences learner engagement, satisfaction, and perceived learning outcomes. While satisfaction with course design and content is high, limited instructor and peer interaction remains a challenge. Overall, the study underscores the potential of AI-enabled personalization to enhance the effectiveness of MOOCs by fostering more engaging and learner-centered online learning experiences.

However, the study emphasizes that AI should not replace human educators but rather complement them through a Hybrid Intelligence model. Such a model leverages the scalability and efficiency of AI while preserving the critical judgment, empathy, and ethical oversight of human instructors

(Kong et al., 2022). Responsible implementation of AI-driven personalization, guided by pedagogical principles and ethical considerations, is essential for building inclusive and effective digital learning ecosystems.

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