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HOW ARTIFICIAL INTELLIGENCE SHAPES TRUST, PERSONALIZATION, AND LEARNER ENGAGEMENT IN HIGHER EDUCATION MOOCS: EVIDENCE FROM A DEVELOPING COUNTRY

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ABSTRACT

Aim/Purpose	Despite the persistent challenge of low learner engagement in Massive Open Online Courses (MOOCs), particularly in Global South contexts, this study examines how artificial intelligence (AI)–enabled learning experiences shape multidimensional learner engagement in higher education MOOCs in Vietnam, based on an extended UTAUT2 framework. Specifically, it investigates the mediating role of behavioral intention in linking AI-enabled experiences to cognitive, emotional, and behavioral engagement.
Background	Although MOOCs expand access to higher education, sustaining meaningful learner engagement remains a persistent challenge. Recent advances in artificial intelligence enable adaptive feedback, intelligent support, and personalized learning pathways; however, limited empirical research explains how these AI-enabled experiences translate into cognitive, emotional, and behavioral engagement, particularly in Global South settings such as Vietnam.
Methodology	A sequential explanatory mixed-methods design was employed. Survey data from 652 MOOC learners in Vietnam (undergraduate students) were analyzed using structural equation modeling to test an integrated motivational–experiential framework. Semi-structured interviews with seven participants provided qualitative insights that explained the structural relationships and captured learners' lived experiences with AI-supported learning.
Contribution	This study develops an integrated framework to explain learner engagement in AI-enhanced MOOCs by extending the UTAUT2 model with AI-specific constructs, including trust in AI and perceived personalization. It reconceptualizes

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technology acceptance factors as functional learning motivations and socio-affective drivers in the context of AI-supported learning. Furthermore, it identifies behavioral intention as a central mediating mechanism linking AI-enabled experiences to multidimensional learner engagement.

Findings AI-enabled learning experiences, together with functional learning motivations and socio-affective drivers, were significantly associated with learners' behavioral intention, which functioned as the central mediating mechanism leading to behavioral, emotional, and cognitive engagement. Among the antecedents, trust in AI, perceived personalization, and hedonic motivation emerged as the strongest predictors of behavioral intention. Qualitative findings further revealed that learners experienced AI as an epistemic and affective partner that fostered metacognitive reflection, structured learning routines, and sustained motivation. However, the effectiveness of AI-enhanced MOOCs was conditioned by infrastructural limitations, uneven digital literacy, and socio-cultural learning contexts.

Recommendations for Practitioners MOOC providers should design transparent, trustworthy, and personalized AI features that support self-regulated learning while ensuring low-bandwidth accessibility and contextual relevance for diverse learner populations.

Recommendations for Researchers Future studies should adopt longitudinal and cross-cultural designs and integrate learning analytics with self-reported engagement measures to capture the dynamic nature of learner–AI interaction.

Impact on Society By identifying mechanisms that foster sustained engagement in large-scale online learning, this study contributes to more inclusive and equitable access to higher education in developing countries.

Future Research Further research may examine experiential AI-supported learning interventions, participatory AI design with learners, and comparative analyses across Global South contexts.

Keywords artificial intelligence, MOOCs, trust in AI, perceived personalization, learner engagement, developing country, UTAUT2

INTRODUCTION

Digital learning platforms have expanded access to higher education, particularly through MOOCs, which offer scalable and flexible learning opportunities in developing countries such as Vietnam (Alraimi et al., 2015). However, while MOOCs promise to reduce educational inequality, their effectiveness remains limited by low learner engagement and high dropout rates (Jordan, 2015; Liyanagunawardena et al., 2013; Zheng et al., 2015).

Despite increasing internet access across the Global South, including Vietnam, sustained engagement in MOOCs remains a persistent challenge (Wei et al., 2024; Zheng et al., 2015). Completion rates often fall, with many learners disengaging early. These issues are exacerbated in regions such as Southeast Asia, particularly Vietnam – an illustrative example of the Global South – due to limited digital literacy, infrastructural instability, and cultural misalignment with course content (Jitpaisarnwattana & Gafaro, 2024; Zheng et al., 2015). Moreover, most MOOC platforms adopt a generic design, neglecting to accommodate the varied educational requirements and socio-economic circumstances of disadvantaged students (Jitpaisarnwattana & Gafaro, 2024).

Learner engagement, in this study, refers to a multidimensional construct encompassing behavioral (e.g., course activity, participation), cognitive (e.g., investment in learning tasks), and emotional (e.g., interest and motivation) dimensions. Enhancing engagement is crucial for improving learning outcomes and increasing completion rates, especially in MOOCs, where instructor presence and peer accountability are limited (Liu et al., 2025; Wei et al., 2024).

Recent advances in AI offer new opportunities to address these challenges. Tools such as intelligent tutoring systems, adaptive feedback, chatbots, and personalized recommendation engines have shown potential to support learner motivation and engagement (X. Chen et al., 2025). However, most existing research focuses on AI in general e-learning environments, with limited empirical work examining how these technologies function within MOOCs, particularly in developing country contexts (Rizwan et al., 2025). Despite the potential of AI, there is limited empirical understanding of how specific AI-driven features influence learner engagement in the unique socio-technical context of developing nations.

To address this gap, this study examines how functional learning motivations, socio-affective drivers, and AI-enabled learning experiences jointly shape learners' behavioral intention and their subsequent behavioral, emotional, and cognitive engagement in higher education MOOCs, especially in developing country contexts where universities are adopting online modalities as the primary method of education delivery (X. Chen et al., 2025; Le & Ho, 2026; Rizwan et al., 2025). Vietnam and comparable Southeast Asian contexts have experienced a sharp increase in MOOC enrollment due to expanding internet infrastructure and strong governmental pushes toward digital education. However, disparities in digital readiness and contextual fit continue to hinder learner retention and success (Pham, 2025; Selwyn, 2022).

This study adopts a mixed-methods approach, integrating quantitative survey-based measures of engagement with qualitative insights from interviews and focus groups. The study examines learners' perceptions of AI-enabled learning experiences, such as adaptive feedback, personalized recommendations, and intelligent support, and how these experiences interact with motivational and socio-affective factors to influence engagement outcomes.

Informed by technology acceptance research, particularly the UTAUT2 model (Venkatesh et al., 2012), this study develops a motivational–experiential framework to explain AI-enabled learner engagement in MOOCs. In this framework, functional learning motivations, socio-affective drivers, and AI-enabled learning experiences are reconceptualized as complementary pathways that shape learners' behavioral intention and, in turn, their multidimensional engagement. This study poses the following research questions to direct the investigation:

- **RQ1.** How do AI-enabled learning experiences influence learners' behavioral intention in MOOCs?
- **RQ2.** How does behavioral intention mediate the relationship between AI-enabled experiences and multidimensional learner engagement?
- **RQ3.** How do functional learning motivations and socio-affective drivers interact with AI-enabled experiences to shape engagement outcomes?

This work enhances the expanding corpus of research on artificial intelligence and online education by: (1) reconceptualizing AI-enabled MOOCs as a motivational–experiential engagement system; (2) offering an integrated explanation of how functional, socio-affective, and AI-mediated learning mechanisms jointly shape multidimensional learner engagement; and (3) providing context-sensitive evidence from the Global South to extend engagement research in low-resource higher education environments. Ultimately, this work supports global efforts toward Sustainable Development Goal 4, which advocates inclusive, equitable, and high-quality education for all, highlighting the transformative impact of AI on the future of digital education in resource-limited environments. The findings are expected to inform the design of scalable, context-sensitive, AI-supported MOOCs and offer practical implications for institutional policymakers aiming to expand digital education in developing regions.

The structure of this paper is as follows. The next section reviews prior literature, while the following section outlines the conceptual framework and research hypotheses. The methodology is explained, and the results are presented, covering quantitative and qualitative analyses. The following section discusses the findings. Finally, the paper concludes with implications and directions for future research.

LITERATURE REVIEW

MOOCS AND LEARNER ENGAGEMENT IN DEVELOPING CONTEXTS

MOOCs provide scalable learning opportunities, particularly in developing countries where access to higher education is constrained. However, despite their potential, empirical research consistently highlights persistent engagement challenges, including low completion rates and declining learner motivation (Berde et al., 2024; Hew & Cheung, 2014; Jordan, 2015; Liyanagunawardena et al., 2013). In Southeast Asia, particularly in Vietnam, recent studies report rapid growth in MOOC adoption driven by digital transformation initiatives and the integration of platforms such as Coursera into higher education (Ho et al., 2022, 2023). Empirical evidence further highlights the importance of social influence, facilitating conditions, and learner motivation in shaping adoption and engagement. At the same time, persistent challenges related to digital literacy, infrastructure, and contextual alignment continue to hinder sustained participation (Venkatesh et al., 2012).

Learner engagement – a critical predictor of persistence and success in MOOCs – is often described in terms of three interrelated dimensions: behavioral, emotional, and cognitive (Fredricks et al., 2004; Yang & Ghislandi, 2024). Behavioral engagement refers to participation in course activities; emotional engagement relates to learners' affective responses (e.g., interest or frustration); and cognitive engagement involves the investment in learning and the use of deep learning strategies. In developing countries, challenges such as an absence of digital literacy, unreliable connectivity, and misaligned content can negatively affect all three engagement dimensions (Selwyn, 2022). These structural and pedagogical barriers are particularly pronounced in higher education MOOCs, where learners must navigate self-directed online environments with minimal institutional support (Hao & Tasir, 2024; Rizwan et al., 2025).

From a motivational perspective, Self-Determination Theory (SDT) explains learner engagement through intrinsic and extrinsic motivation, emphasizing autonomy, competence, and relatedness (Deci & Ryan, 2000). In AI-enhanced MOOCs, features such as personalization and adaptive feedback may support these psychological needs by enabling greater learner control and providing competence-related feedback. This aligns conceptually with constructs such as hedonic motivation, which reflects intrinsic enjoyment in technology use (Venkatesh et al., 2012).

Flow Theory further explains deep engagement in technology-mediated environments, suggesting that optimal learning occurs when there is a balance between perceived challenge and individual skill, leading to immersive, sustained interaction (Csikszentmihalyi, 1990). AI systems, through adaptive task difficulty and real-time feedback, have the potential to facilitate such conditions, thereby supporting sustained engagement in online learning contexts.

In addition, Self-Regulated Learning (SRL) is central to success in MOOCs, where learners are required to manage their learning processes (Zimmerman, 2002) independently. AI-supported tools, such as learning analytics dashboards and personalized recommendations, may enhance learners' ability to plan, monitor, and regulate their learning activities. This suggests a complementary relationship between AI affordances and SRL processes in supporting learner engagement.

Despite these theoretical perspectives, limited research has integrated motivational, cognitive, and AI-enabled learning factors into a unified framework to explain multidimensional engagement in MOOCs, particularly in developing country contexts. This gap highlights the need for an integrative approach that connects technology adoption, motivational processes, and AI-enabled learning experiences.

AI IN ONLINE LEARNING AND MOOCS

AI technologies have been increasingly integrated into educational settings to deliver personalized, responsive, and scalable learning experiences. Instruments such as intelligent tutoring systems, adaptive feedback, and AI-driven support features have demonstrated the ability to increase motivation and support learner persistence (L. Chen et al., 2020; Khosravi et al., 2022). In the MOOC setting, AI can be leveraged to address engagement challenges in MOOCs through features such as content recommendation engines, learning analytics dashboards, and emotion-aware interfaces (Becerra et al., 2024; Bhatt & Muduli, 2024; Sunar et al., 2016).

Despite these advances, empirical research examining how AI-enabled features translate into multidimensional learner engagement in MOOCs remains limited, particularly in developing country contexts. Existing studies often focus on system design or theoretical affordances, providing limited insight into how learners perceive, trust, and interact with AI-supported learning in real-world environments (Rana et al., 2024; Sunar et al., 2016; Zawacki-Richter et al., 2019). Moreover, limited research has empirically validated how AI features impact each dimension of learner engagement in MOOCs, particularly through theoretically grounded models tailored to low-resource higher education contexts (Wei et al., 2024). In particular, trust in AI and perceived personalization remain underexplored, despite their potential to shape learners' behavioral intention and engagement in AI-enhanced learning environments, though they may strongly influence user intentions and actual engagement (Agatova & Latipova, 2025; Rana et al., 2024).

Beyond functional benefits, the application of AI in education raises ethical concerns, including algorithmic bias, data privacy, and transparency (Zawacki-Richter et al., 2019). These concerns are particularly salient in developing contexts, where uneven access to technological resources may exacerbate existing inequalities. Such issues can influence learners' trust in AI systems, which in turn may affect their willingness to engage with AI-enabled learning environments. These gaps highlight the need for a theoretically grounded framework that integrates AI-enabled learning experiences, motivational factors, and trust-related mechanisms to explain learner engagement in MOOCs.

THEORETICAL FOUNDATION AND RESEARCH MODEL DEVELOPMENT

Building on the reviewed literature, this section develops the conceptual framework and research hypotheses of the study. To understand how learners in developing countries adopt and engage with AI-enhanced MOOCs, this study draws on technology acceptance research, particularly UTAUT2 (Venkatesh et al., 2012), to reconceptualize learners' engagement with AI-enhanced MOOCs as a motivational–experiential process (Dwivedi et al., 2021). While UTAUT2 has been widely used to explain technology adoption, this study extends its application by reinterpreting its core constructs as functional learning motivations and socio-affective drivers in AI-supported learning contexts.

To reflect the distinctive characteristics of AI-supported learning, this study incorporates trust in AI and perceived personalization as key dimensions of AI-enabled learning experience. These constructs reflect learners' confidence in the reliability and fairness of AI tools and the degree to which the system customizes material and learning trajectories to meet individual requirements – two factors that are especially important in low-resource, culturally diverse contexts (L. Chen et al., 2020; Rana et al., 2024; Zawacki-Richter et al., 2019). The inclusion of these variables addresses key psychological and contextual factors that have been underexplored in previous acceptance studies within AI-supported online learning (Dwivedi et al., 2021).

The proposed model conceptualizes behavioral intention as a motivational readiness that mediates relationships among these three complementary pathways and learners' behavioral, emotional, and cognitive engagement (Fredricks et al., 2004; Venkatesh et al., 2012). This conceptualization extends prior technology acceptance research by positioning behavioral intention not only as a predictor of usage but also as a key mechanism linking AI-enabled experiences to multidimensional engagement outcomes. Accordingly, engagement is not treated merely as an outcome of technology use but as a dynamic learning process shaped by interacting motivational and experiential pathways. This integration provides a more comprehensive and actionable understanding of how learners engage with AI-supported online learning environments.

By integrating established technology acceptance theory with AI-relevant extensions and engagement outcomes, the proposed model offers a context-sensitive framework to explore how AI can support more inclusive and effective learning experiences in higher education MOOCs, particularly for underrepresented learners in Southeast Asia.

Despite growing interest in AI-supported learning, existing research remains fragmented, often lacking integration between motivational theories, AI-enabled features, and multidimensional engagement outcomes. Addressing this gap, this study proposes an integrated framework that links functional motivations, socio-affective drivers, and AI-enabled learning experiences to learner engagement in MOOCs.

FRAMEWORK MODEL AND HYPOTHESES

FRAMEWORK MODEL

This study's conceptual framework is informed by technology acceptance research, particularly UTAUT2 (Venkatesh et al., 2012), and reconceptualizes its core constructs as functional learning motivations and socio-affective drivers within AI-enabled MOOC environments (Figure 1).

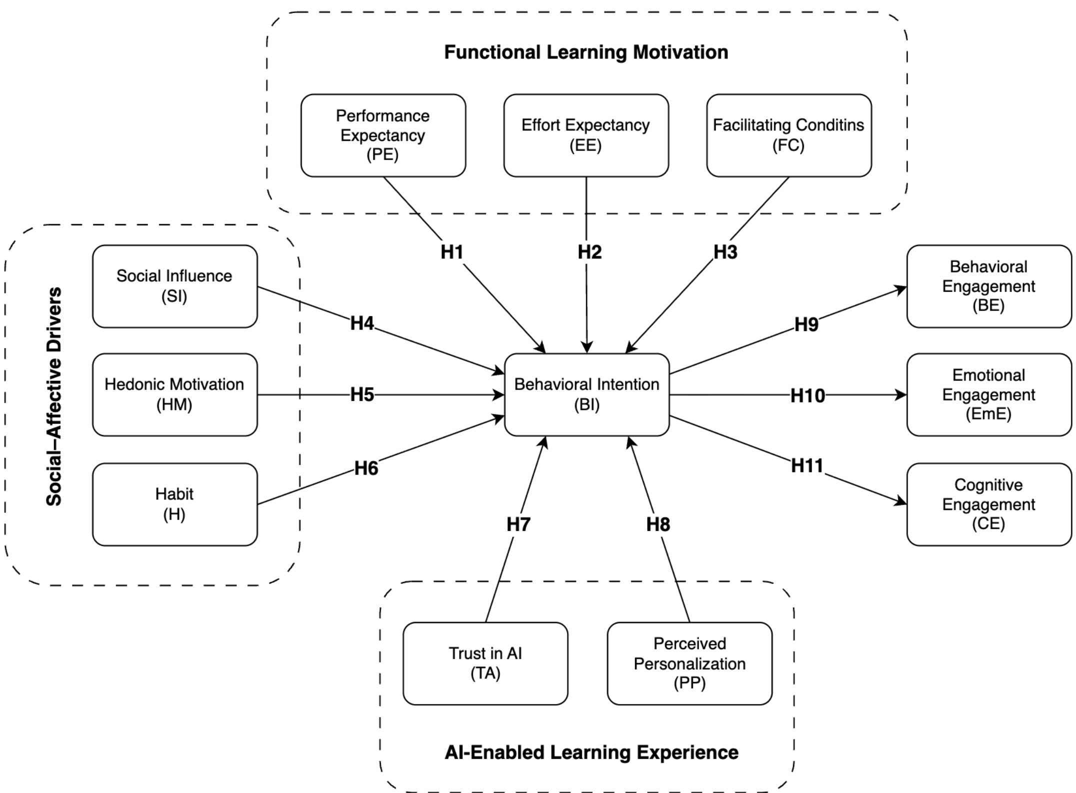

Figure 1. Conceptual framework of the study

The model illustrates the influence of functional, socio-affective, and AI-enabled learning pathways on behavioral intention (BI), which in turn affects three types of user engagement: behavioral, emotional, and cognitive.

To address the unique context of AI-enhanced MOOCs in developing countries, the model is augmented by integrating two supplementary constructs – Trust in AI (TA) and Perceived Personalization (PP) – both of which reflect the distinct affordances and user concerns associated with intelligent learning systems (L. Chen et al., 2020; Truong et al., 2024; Zawacki-Richter et al., 2019).

The fundamental element of the model is Behavioral Intention (BI), conceptualized as learners' motivational readiness (Venkatesh et al., 2012) and shaped by three complementary pathways: functional learning motivations, socio-affective drivers, and AI-enabled learning experiences (Dwivedi et al., 2021). These pathways are operationalized through eight constructs in the empirical model.

These variables represent both different dimensions of learners' motivational and experiential processes and emerging user concerns in intelligent learning systems. These factors are posited to affect learners' intention to utilize AI-enhanced MOOC systems. Subsequently, BI is posited to affect three dimensions of learner engagement: Behavioral Engagement (BE), Emotional Engagement (EmE), and Cognitive Engagement (CE) (Fredricks et al., 2004). This approach is especially crucial for comprehending AI-assisted learning in higher education MOOCs in low-resource settings, where learner engagement and system acceptance are often challenged by infrastructural, pedagogical, and cultural barriers (Selwyn, 2022; Zawacki-Richter et al., 2019).

Hypotheses

The hypotheses presented below outline the theorized relationships among the constructs representing functional learning motivations (PE, EE, FC) and social-affective drivers (SI, HM, H), as well as AI-enabled learning experience factors (TA, PP), and learner engagement outcomes (BE, EmE, CE). These hypotheses are grounded in prior research and adapted to the contextual realities of higher education MOOCs in developing countries. In line with the proposed framework, these relationships reflect how different motivational and experiential pathways contribute to learners' readiness to engage with AI-enhanced MOOCs.

Performance Expectancy (PE) is characterized as the extent to which learners perceive that using AI-enhanced MOOC platforms will enhance their academic performance and learning results (Islam et al., 2024). Prior research has consistently shown that when users perceive a system as beneficial to their goals, they are more inclined to adopt it (Venkatesh et al., 2012). In higher education settings, performance-driven learners are especially sensitive to perceived academic benefits, making PE a key determinant of adoption.

> **H1:** PE is positively associated with learners' BI to use AI-enhanced MOOCs.

Effort Expectancy (EE) denotes the perceived simplicity of utilizing a system. Students are more inclined to embrace and utilize AI systems when they regard them as intuitive, easy to use, and requiring low cognitive exertion (Alyoussef et al., 2025; Venkatesh et al., 2012). Given the digital skill gaps in many developing-country higher education systems, user-friendly AI interfaces are crucial for engagement.

> **H2:** EE is positively associated with learners' BI to use AI-enhanced MOOCs.

Facilitating Conditions (FC) include the accessibility of resources, infrastructure, and institutional or technical support needed to effectively use the technology (Moradi, 2025; Venkatesh et al., 2012). Institutional readiness, including digital policies and help-desk support, is particularly critical for learners navigating AI-enhanced higher education platforms. While prior research generally conceptualizes facilitating conditions as enabling factors, their role may vary depending on contextual constraints, particularly in developing-country settings.

> **H3:** FC is positively associated with learners' BI to use AI-enhanced MOOCs.

Social Influence (SI) encompasses the degree to which learners recognize the significance of others, such as peers, educators, or institutional authorities, who encourage or expect them to use AI-enabled features (Almogren et al., 2024; Perez, 2024; Venkatesh et al., 2012). In university environments, peer norms and faculty endorsement can play a decisive role in technology adoption.

H4: SI is positively associated with learners' BI to use AI-enhanced MOOCs.

Hedonic Motivation (HM) pertains to the delight or intrinsic satisfaction obtained from utilizing a system. Engaging AI tools, such as gamified learning paths, conversational chatbots, or interactive feedback, can make learning experiences more enjoyable, thereby encouraging sustained usage (Li & Lin, 2025; Qu & Wu, 2024; Venkatesh et al., 2012). Intrinsic enjoyment can be a powerful driver of voluntary participation in AI-supported online courses.

H5: HM is positively associated with learners' BI to use AI-enhanced MOOCs.

Habit (H) indicates the degree to which learners have assimilated the utilization of AI tools into their regular learning behavior through repeated exposure and familiarity (Sun, 2025; Venkatesh et al., 2012). In institutionalized MOOC environments, prior exposure to similar digital tools can reinforce habitual use. However, in emerging AI-supported learning contexts, habitual use may not yet be fully established, particularly among learners with limited prior exposure to such technologies.

H6: H is positively associated with learners' BI to use AI-enhanced MOOCs.

Trust in AI (TA) is conceptualized as learners' belief that AI features are reliable, transparent, secure, and operate in their optimal interest. Trust is a critical enabler in educational contexts where decisions (e.g., feedback, recommendations) are automated. A lack of trust may lead to rejection, regardless of perceived usefulness (Jacques et al., 2024; Rana et al., 2024; Zawacki-Richter et al., 2019). Trust becomes especially important in AI-enhanced platforms where learners rely on opaque algorithms to guide their learning.

H7: TA is positively associated with learners' BI to use AI-enhanced MOOCs.

Perceived Personalization (PP) refers to the extent to which learners recognize that the platform tailors content, recommendations, or feedback to their individual learning goals, preferences, or progress (Sunar et al., 2016; Truong et al., 2024). In MOOCs, adaptive personalization may compensate for the lack of real-time human instruction, enhancing learner motivation.

H8: PP is positively associated with learners' BI to use AI-enhanced MOOCs.

Behavioral Engagement (BE) refers to observable actions such as logging into the platform, submitting assignments, completing quizzes, or participating in forums. Learners with high behavioral intention are more likely to exhibit these active behaviors (X. Chen et al., 2025; Fredricks et al., 2004; Venkatesh et al., 2012). Such behavioral indicators are essential for tracking learner progress and predicting MOOC completion.

H9: BI is positively associated with learners' BE.

Emotional Engagement (EmE) encompasses learners' affective responses, such as enjoyment, interest, and emotional connection to the learning experience (Fredricks et al., 2004; Ilyas et al., 2025; Kovari, 2025). AI systems that offer encouragement, reminders, or emotionally resonant content can strengthen affective bonds between the learner and the platform.

H10: BI is positively associated with learners' EmE.

Cognitive Engagement (CE) entails the application of profound learning strategies, metacognitive reflection, and sustained mental effort. Platforms that promote reflection, offer tailored scaffolding, or track metacognitive behavior can deepen learners' cognitive involvement (Bauer et al., 2025; Fredricks et al., 2004; McClure et al., 2024).

H11: BI is positively associated with learners' CE.

METHODOLOGY

This study adopted a sequential explanatory mixed-methods approach to explore how AI influences learner engagement in MOOCs, particularly in developing country contexts (Takona, 2024). This study design was chosen to address the intricate, multifaceted nature of engagement by integrating the statistical generalizability of quantitative analysis with the contextual richness of qualitative insights. Participation was voluntary, and all participants provided informed consent before data collection. Participants were informed about the purpose of the study, the procedures involved, their right to withdraw at any time without penalty, and the confidentiality of their responses. No personally identifiable information was collected, and all data were anonymized and used solely for research purposes.

THEORETICAL FOUNDATION AND INSTRUMENT DEVELOPMENT

The study began by identifying key problems related to low MOOC engagement rates in AI-integrated environments. A rigorous literature review and theoretical analysis informed the creation of a conceptual framework grounded in the UTAUT2 model and the AI interaction literature. Vietnam was selected as a representative Southeast Asian context due to its rapid expansion of digital education and emerging adoption of MOOCs in higher education, yet with persistent challenges in infrastructure and digital equity. Based on this framework, measurement instruments were designed separately for both the quantitative and qualitative components (Takona, 2024). Preliminary instruments were constructed using validated items adapted from existing scales (e.g., Venkatesh et al., 2012) and enriched by recent studies on AI-supported learning environments.

QUANTITATIVE PHASE

The questionnaire was originally developed in English and translated into Vietnamese. The translation process was carefully conducted to ensure linguistic accuracy and conceptual equivalence, with iterative refinement based on careful review. A structured survey was administered in two stages. A pilot study with 26 participants was conducted to test reliability and clarity, with minor revisions made based on participant feedback. Items with low Cronbach's Alpha (< 0.70), low factor loading (< 0.60), or corrected item-total correlation (< 0.30) were removed (DeVellis, 2017; Hair et al., 2019). Following validation, the main survey was deployed, yielding 678 initial responses. After data screening and removal of invalid entries, a final dataset of 652 responses was retained for analysis.

Data were collected using both online and offline methods at several universities in Vietnam that have implemented MOOCs in their curriculum. This dual-mode approach ensured broader representation across urban and semi-urban student groups, reflecting varying levels of infrastructure and digital exposure. A convenience sampling strategy was employed due to the institutional nature of MOOC implementation and the requirement that participants had prior experience with AI-enabled MOOC platforms.

Participants were required to meet two inclusion criteria: (1) current enrollment in a university that integrates MOOCs into its curriculum, and (2) prior experience using AI-enabled features within MOOC platforms. The final sample ($N = 652$) consisted primarily of undergraduate students, reflecting the target population of MOOC-integrated higher education programs in Vietnam, with a balanced gender distribution (49.23% female, 49.54% male, and 1.23% other), and diverse academic disciplines.

The survey instrument consisted of 48 items measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), covering twelve constructs: PE, EE, FC, SI, HM, H, TA, PP, BI, BE, EmE, and CE. Each construct was measured using four items adapted from prior validated scales. The full list of survey items is provided in Appendix A to ensure transparency and replicability.

Quantitative data were analyzed using SPSS 25.0 and AMOS 20.0. The analysis began with descriptive statistics and demographic profiling, followed by reliability assessment and exploratory factor analysis (EFA). To examine the potential presence of common method bias (CMB), Harman's single-factor test was applied (Podsakoff et al., 2003). The results indicated that the first factor explained less than 50% of the total variance, suggesting that common method bias was not a major concern. Subsequently, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were conducted to evaluate construct validity and test the hypothesized relationships (Hair et al., 2019).

QUALITATIVE PHASE

Following the quantitative phase, semi-structured interviews were conducted with MOOC learners who had experience using AI features such as adaptive feedback, chatbot support, or personalized recommendations. Participants for the qualitative phase were recruited from the same pool as the survey respondents. A total of 11 participants initially volunteered for the interview phase. From this pool, seven participants were purposively selected based on their level of engagement and demonstrated experience with AI-enabled MOOC features (e.g., frequent use of adaptive feedback, recommendations, or AI-supported tools). This purposive selection ensured that participants could provide rich, relevant, and experience-based insights aligned with the study's objectives.

The interview protocol was structured into three sections to capture learners' experiences comprehensively. Section 1 collected general background information, including participants' country, academic background, MOOC experience, and prior use of AI tools in online learning environments. Section 2 explored learners' experiences with AI-enabled MOOC features, organized around key constructs of the research model. Questions addressed perceived usefulness, ease of use, social influence, technical conditions, enjoyment, habitual use, trust in AI, perceived personalization, future intention, and multidimensional engagement (behavioral, emotional, and cognitive). Participants were encouraged to provide concrete examples to illustrate their experiences. Section 3 invited reflective feedback, asking participants to provide recommendations for improving AI integration in MOOCs and share additional insights. The full interview guide is provided in Appendix B.

The qualitative data were analyzed using reflexive thematic analysis following Braun and Clarke (2006), emphasizing a reflexive and iterative coding process. The analysis followed six phases: (1) data familiarization, (2) initial code generation, (3) theme development, (4) theme review, (5) theme definition and naming, and (6) report production. To enhance analytical rigor, the coding process followed an iterative and reflexive approach, involving repeated engagement with the data to refine codes and themes and ensure analytical coherence. Rather than seeking inter-coder reliability, the analysis emphasized reflexive interpretation, transparency, and analytical depth, consistent with Braun and Clarke (2006, 2021).

Analytical decisions were continuously revisited to ensure coherence between data, codes, and themes. The study ensured qualitative rigor through credibility (use of participant quotations), transparency in coding, and reflexive engagement with the data.

RESULT

DEMOGRAPHIC INFORMATION

A total of 652 valid responses were retained for analysis, as presented in Table 1. The gender distribution was balanced, with 49.54% identifying as male and 49.23% as female, while 1.23% preferred not to disclose. Regarding AI familiarity, 54.14% reported only a basic understanding, 26.23% rated their knowledge as good, 16.56% as average, and 3.07% as highly proficient, suggesting heterogeneous levels of AI experience among respondents. MOOC awareness was widespread, with Coursera recognized by 98.93% of participants, while other platforms such as edX (30.21%) and Udemy (23.62%) showed lower levels of recognition, indicating the dominant presence of Coursera in this context.

In terms of engagement frequency, the majority of participants (85.12%) reported using MOOCs frequently (3–5 times per week), followed by 5.38% who engaged very frequently (daily or almost daily), 8.59% who engaged occasionally (1–2 times per week), and only 0.46% who reported rare usage (less than once per week). This distribution indicates a generally high level of sustained engagement with MOOCs among respondents.

Table 1. Participant demographics and AI-MOOC engagement context

Variables	Category	N = 652	
		Frequency	Percent (%)
What is your gender?	Male	323	49.54%
	Female	321	49.23%
	I do not want to be specific	8	1.23%
How familiar are you with AI tools in general?	Fair	18	2.76%
	Average	90	13.80%
	Basic	353	54.14%
	Good	171	26.23%
	Excellent	20	3.07%
Which MOOC platforms have you used? (select all that apply)	Coursera	645	98.93%
	edX	197	30.21%
	Udemy	154	23.62%
How often do you learn on MOOCs?	Very frequently (daily or almost daily)	38	5.38%
	Frequently (3–5 times per week)	555	85.12%
	Occasionally (1–2 times per week)	56	8.59%
	Rarely (less than once per week)	3	0.46%

Item Statistics and Reliability Analysis

A variety of psychometric assessments were done to evaluate the reliability and validity of the measurement model, including standard deviation (SD), factor loading (FL), item-total correlations (r_it), and Cronbach's alpha (α). Table 2 presents the detailed results for each construct and corresponding items. All standardized factor loadings surpassed the suggested threshold of 0.70 (Hair et al., 2019), indicating strong item reliability. Item-total correlation coefficients also exceeded the acceptable cut-off of 0.30 (Nunnally & Bernstein, 1994), further supporting internal consistency. Cronbach's alpha (α) scores for all constructs varied from 0.815 (TA) to 0.901 (SI), demonstrating good to excellent reliability across constructs. Notably, all study constructs, including newly integrated variables such as TA and PP, achieved strong psychometric properties, confirming the reliability of the measurement instrument.

Table 2. Descriptive statistics, factor loadings, and reliability indicators for measurement items

Variable	Mean	SD	FL	Reliability testing	
				r_it	α
Performance Expectancy (PE)					0.874
PE1	4.01	0.917	0.744	0.654	
PE2	4.01	0.900	0.747	0.742	
PE3	3.87	0.966	0.707	0.759	
PE4	3.93	0.997	0.726	0.766	

Variable	Mean	SD	FL	Reliability testing	
				r_{it}	α
Effort Expectancy (EE)					0.875
EE1	3.53	0.952	0.854	0.751	
EE2	3.56	0.933	0.845	0.724	
EE3	3.53	0.987	0.844	0.729	
EE4	3.52	0.970	0.845	0.723	
Social Influence (SI)					0.901
SI1	3.62	0.974	0.784	0.761	
SI2	3.67	0.969	0.791	0.725	
SI3	3.71	0.930	0.810	0.802	
SI4	3.71	0.929	0.854	0.829	
Facilitating Conditions (FC)					0.843
FC1	3.61	0.827	0.711	0.666	
FC2	3.56	0.841	0.738	0.647	
FC3	3.59	0.820	0.760	0.710	
FC4	3.73	0.750	0.789	0.692	
Hedonic Motivation (HM)					0.861
HM1	3.71	0.896	0.786	0.676	
HM2	3.72	0.877	0.772	0.710	
HM3	3.71	0.877	0.762	0.704	
HM4	3.80	0.892	0.786	0.742	
Habit (H)					0.884
H1	3.65	1.005	0.733	0.748	
H2	3.73	0.895	0.761	0.694	
H3	3.69	0.926	0.799	0.777	
H4	3.59	0.915	0.804	0.774	
Trust in AI (TA)					0.815
TA1	4.01	0.932	0.743	0.561	
TA2	4.07	0.904	0.783	0.652	
TA3	3.91	0.969	0.747	0.662	
TA4	4.03	0.977	0.767	0.668	
Perceived Personalization (PP)					0.837
PP1	3.71	1.031	0.752	0.666	
PP2	3.73	0.940	0.758	0.610	
PP3	3.73	0.964	0.803	0.693	
PP4	3.63	0.958	0.815	0.704	
Behavioral Intention (BI)					0.870
BI1	3.62	0.960	0.781	0.715	
BI2	3.58	1.018	0.783	0.669	
BI3	3.64	0.939	0.804	0.740	
BI4	3.64	0.961	0.826	0.769	

Variable	Mean	SD	FL	Reliability testing	
				r_{it}	α
Behavioral Engagement (BE)					0.850
BE1	3.74	0.967	0.789	0.666	
BE2	3.70	0.957	0.821	0.686	
BE3	3.69	0.953	0.836	0.730	
BE4	3.78	0.951	0.808	0.678	
Emotional Engagement (EmE)					0.840
EmE1	3.83	0.899	0.774	0.634	
EmE2	3.80	0.934	0.806	0.669	
EmE3	3.83	0.916	0.764	0.657	
EmE4	3.87	0.924	0.829	0.732	
Cognitive Engagement (CE)					0.896
CE1	3.75	0.702	0.841	0.755	
CE2	3.78	0.743	0.841	0.761	
CE3	3.80	0.751	0.838	0.740	
CE4	3.80	0.711	0.882	0.824	

To evaluate the construct structure and assess the sufficiency of the measurement model, Exploratory factor analysis (EFA) was conducted. Furthermore, the Kaiser-Meyer-Olkin (KMO) metric of sample adequacy was 0.884, demonstrating a commendably elevated degree of shared variance among the variables (Kaiser, 1974). Furthermore, Bartlett's test of sphericity yielded a statistically significant result ($p < 0.001$), indicating that the correlation matrix was not an identity matrix and was therefore appropriate for factor analysis (Bartlett, 1950). The eigenvalues (λ) and the cumulative variance explained by the twelve extracted factors were examined. All twelve factors reported eigenvalues above the Kaiser criterion of 1.0 (Kaiser, 1974), confirming their statistical significance and justifying retention in the measurement model. The twelve factors collectively represented 72.01% of the overall variation, surpassing the suggested threshold of 50% (Hair et al., 2019), supporting the adequacy of the factor structure. Harman's single-factor test indicated that the first factor accounted for 21.360% of the total variance, which is below the 50% threshold, suggesting that CMB is unlikely to pose a serious threat to the validity of the results (Harman, 1976).

Confirmatory Factor Analysis

To evaluate the adequacy of the measurement model, the results indicate that the measurement model fits the data well: the χ^2/df value was 1.850, below the suggested threshold of 3.0, indicating a good fit between the proposed model and the observed data. The acceptable threshold of 0.90 was surpassed by both the CFI (Comparative Fit Index) = 0.949 and TLI (Tucker–Lewis Index) = 0.944, indicating a strong incremental fit (Bentler, 1990; Hu & Bentler, 1999; Tucker & Lewis, 1973). Moreover, the RMSEA (Root Mean Square Error of Approximation) was 0.036 (below 0.06), indicating that the model provides an excellent approximation to the population data, while the PCLOSE value of 1.000 (PCLOSE $\geq$ 0.05) further confirmed that the model did not exhibit significant approximation error. Collectively, these indices support the conclusion that the measurement model exhibits an exceptional overall fit.

The composite reliability (CR) values ranged from 0.817 to 0.903, while the average variance extracted (AVE) ranged from 0.528 to 0.699. All constructs surpassed the recommended thresholds of CR > 0.70 and AVE $\geq$ 0.50 (Fornell & Larcker, 1981; Hair et al., 2019), indicating that the measurement items were internally consistent and effectively represented their respective latent constructs. Constructs such as SI and CE demonstrated particularly high reliability and convergence, with CR and AVE values reaching 0.903 and 0.699, respectively. Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of each construct's AVE be greater than its highest correlation with any other construct (Fornell & Larcker, 1981). The results confirmed that this condition was met for all constructs, with the square roots of AVE ranging from 0.727 to 0.836, consistently higher than the corresponding inter-construct correlations (Table 3). This finding indicates that the constructs are empirically distinct.

Table 3. Discriminant validity assessment (Fornell–Larcker Criterion)

	CE	PE	EE	SI	FC	HM	H	TA	PP	BI	BE	EmE
CE	**0.828**											
PE	0.331	**0.799**										
EE	-0.162	-0.063	**0.798**									
SI	0.227	0.546	-0.082	**0.836**								
FC	0.193	0.583	-0.005	0.526	**0.759**							
HM	0.231	0.561	-0.074	0.455	0.519	**0.781**						
H	0.235	0.657	-0.067	0.493	0.614	0.464	**0.812**					
TA	0.209	0.110	-0.008	0.092	0.034	0.117	0.061	**0.727**				
PP	0.159	0.065	0.035	0.115	0.038	0.019	0.049	0.562	**0.751**			
BI	0.278	0.331	0.094	0.318	0.174	0.350	0.277	0.353	0.369	**0.793**		
BE	0.138	0.236	-0.082	0.227	0.161	0.221	0.235	0.205	0.200	0.265	**0.767**	
EmE	0.129	0.304	-0.108	0.256	0.221	0.226	0.279	0.330	0.235	0.314	0.168	**0.755**

Note: The bolded diagonal elements in the correlation matrix represent the square roots of AVE (√AVE) for each construct.

Structural Equation Modeling

The structural model exhibited a satisfactory overall fit, as shown in Table 4. The chi-square/df (χ^2/df) ratio was 1.958 (χ^2/df < 3), indicating an acceptable model fit. Both CFI (0.942) and TLI (0.937) exceeded the recommended cutoff of 0.90, indicating a strong incremental fit (Bentler, 1990; Hu & Bentler, 1999; Tucker & Lewis, 1973). Moreover, the RMSEA was 0.038 (RMSEA < 0.06), and PCLOSE was 1.000 (PCLOSE ≥ 0.05), indicating a close fit between the proposed model and the empirical data. Overall, these fit indices suggest that the structural model is statistically robust and appropriate for hypothesis testing.

Table 4. Structural model fit summary

Model fit statistics	χ^2/df	CFI	TLI	RMSEA	PCLOSE
Analysis results	1.958	0.942	0.937	0.038	1.000
Recommended thresholds	≤ 3	≥ 0.9	≥ 0.9	≤ 0.06	≥ 0.05

The structural model provided empirical support for most of the proposed hypotheses, as shown in Table 5. Several factors significantly influenced Behavioral Intention (BI) ($p \leq 0.05$). Specifically, Perceived Personalization (PP → BI, H8) had the strongest positive effect ($\beta = 0.249$, $p < 0.001$), followed by Hedonic Motivation (HM → BI, H5; $\beta = 0.242$, $p < 0.001$), Trust in AI (TA → BI, H7; $\beta = 0.173$, $p < 0.001$), and Social Influence (SI → BI, H4; $\beta = 0.154$, $p < 0.01$). Performance Expectancy (PE → BI, H1; $\beta = 0.137$, $p < 0.05$) and Effort Expectancy (EE → BI, H2; $\beta = 0.115$, $p < 0.01$) were positively associated with behavioral intention. Facilitating Conditions (FC → BI, H3) exerted a significant negative effect ($\beta = -0.181$, $p < 0.01$). The influence of Habit (H → BI, H6) was marginally significant ($\beta = 0.117$, $p = 0.050$). In the second part of the model, BI was significantly associated with all three engagement dimensions: Behavioral Engagement (BI → BE, H9; β = 0.289, $p < 0.001$), Emotional Engagement (BI → EmE, H10; β = 0.341, $p < 0.001$), and Cognitive Engagement (BI → CE, H11; β = 0.300, $p < 0.001$).

Table 5. Hypotheses testing

Hypotheses	Relationships	β	S.E.	p-value	Result
H1	PE → BI	0.137	0.079	0.029	Supported
H2	EE → BI	0.115	0.039	0.003	Supported
H3	FC → BI	-0.181	0.075	0.003	Supported
H4	SI → BI	0.154	0.050	0.002	Supported
H5	HM → BI	0.242	0.065	***	Supported
H6	H → BI	0.117	0.057	0.050	Supported (marginal)
H7	TA → BI	0.173	0.073	***	Supported
H8	PP → BI	0.249	0.055	***	Supported
H9	BI → BE	0.289	0.041	***	Supported
H10	BI → EmE	0.341	0.043	***	Supported
H11	BI → CE	0.300	0.035	***	Supported

Note: S.E = Standard Error, ***$p < 0.001$

R-squared (R^2) values were examined to assess the explanatory power of the structural model. The results indicate that the model explains 35.7% of the variance in BI. For the engagement outcomes, BI accounts for 8.4% of the variance in BE, 11.6% of EmE, and 9.0% of CE. The outcomes of the bootstrapping analysis (95% bias-corrected confidence intervals) are summarized in Table 6, with full results reported in Appendix C.

Most predictors showed significant direct associations with BI, with PP, HM, and TA showing the strongest positive associations, while FC showed a significant negative effect. Although PE showed a significant effect in the structural model (β = 0.137, $p = 0.029$), it was not statistically significant in the bootstrapping analysis ($p = 0.056$), suggesting that this relationship may not be robust. H showed a marginal effect in the structural model ($p = 0.050$) but was not significant in the bootstrapping analysis ($p = 0.102$), indicating limited robustness. BI was significantly associated with all three dimensions of engagement: BE (β = 0.289, $p < 0.01$), EmE (β = 0.341, $p < 0.01$), and CE (β = 0.300, $p < 0.01$). Several indirect effects through BI were also significant. FC also exhibited negative indirect effects on emotional and cognitive engagement, consistent with its negative direct effect in the structural model.

Figure 2 depicts the structural model, which illustrates the proposed relationships among the latent variables. BI functions as the central mediator, receiving direct effects from multiple antecedents and subsequently influencing three types of learner engagement: behavioral, emotional, and cognitive. All measurement items loaded onto their respective constructs, and the model fit indices indicate a good overall fit.

QUALITATIVE ANALYSIS

ANALYTICAL FRAMING

Reflexive thematic analysis (Braun & Clarke, 2006, 2021) was employed to examine learners' lived experiences with AI-enhanced MOOCs. The analysis was theoretically informed by the UTAUT2 framework, constructivist learning theory, and AI adoption literature (Davis, 1989; Venkatesh et al., 2012; Zawacki-Richter et al., 2019).

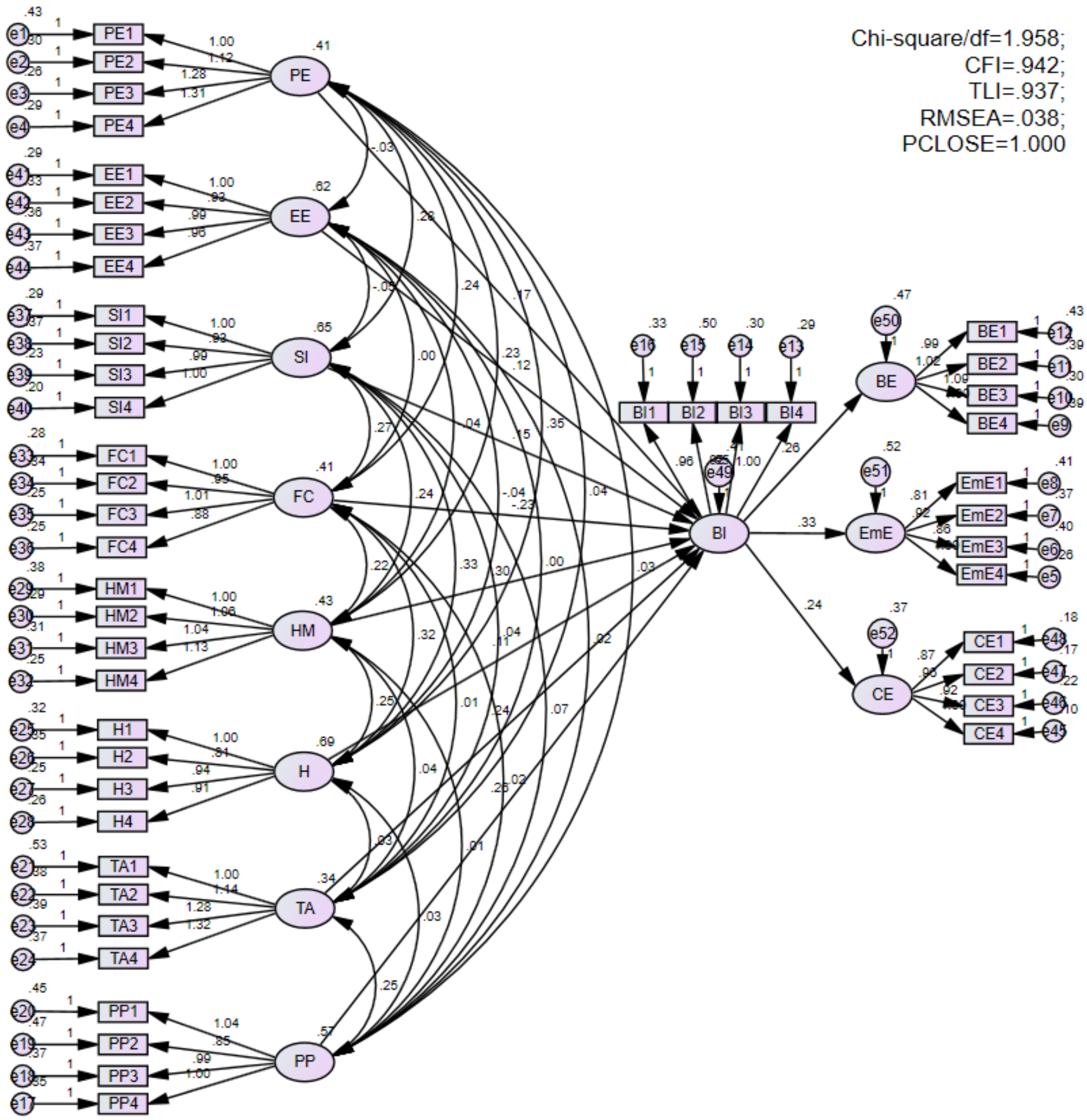

Figure 2. Standardized structural model of the proposed model

Seven interview transcripts were coded inductively and iteratively refined into themes reflecting cognitive, behavioral, and emotional engagement (Fredricks et al., 2004). These themes were analytically linked to the quantitative paths in the structural model, enabling methodological triangulation while preserving interpretive depth.

Key Themes and Interpretive Depth

Meta-theme I: Cognitive engagement – AI as an epistemic partner

Summary. Cognitive engagement emerged as a dominant dimension, with learners perceiving AI as an active epistemic partner that supports understanding, reflection, and knowledge construction.

Performance expectancy – AI scaffolding and epistemic understanding. Participants consistently described AI as supporting conceptual clarification through adaptive explanations and interactive feedback.

> *"AI tools helped clarify some concepts and provided tailored suggestions based on my progress."* (P1)

> *"AI has helped me better understand course content by summarizing complex topics and providing explanations via chatbots."* (P3)

These accounts suggest that AI functions as an epistemic scaffold, enabling learners to elaborate, restructure knowledge, and engage more deeply with course content. This extends performance expectancy beyond functional utility toward a constructivist learning process consistent with prior work on AI-supported learning and knowledge construction (L. Chen et al., 2020; Khosravi et al., 2022).

Perceived personalization – Metacognitive reflection and autonomy. AI-driven personalization enabled learners to identify knowledge gaps and regulate their learning trajectories.

> *"The AI tools provided personalized recommendations based on my progress and areas where I struggled. This made learning more relevant and effective."* (P2)

> *"While not always deeply personalized, the AI's ability to respond to my specific questions made the experience feel tailored and supportive."* (P6)

These findings indicate that personalization fosters metacognitive awareness and learner autonomy, particularly in self-directed MOOC environments, as suggested in AI-driven personalized learning literature (Agatova & Latipova, 2025).

Hedonic motivation – Cognitive–affective reinforcement. Participants reported that AI validation of their ideas enhanced confidence and intellectual satisfaction.

> *"If some of the ideas that AI comes up with match my own, it gives me confidence and direction."* (P7)

This suggests that hedonic motivation emerges from cognitive reinforcement rather than novelty, supporting sustained engagement and behavioral intention, aligning with prior findings on intrinsic motivation in AI learning environments (Li & Lin, 2025; Qu & Wu, 2024).

Effort expectancy – Ease of use and cognitive accessibility. Learners emphasized the intuitive and accessible nature of AI interfaces.

> *"The AI tools were mostly easy to interact with … ChatGPT was simple to use alongside my lessons."* (P4)

> *"AI is mostly user-friendly … but requires some knowledge to use effectively."* (P5)

Perceived ease of use reduces cognitive barriers to adoption, although effective use still depends on basic domain knowledge and prompt literacy, consistent with technology acceptance literature (Venkatesh et al., 2012).

Meta-theme II: Behavioral engagement – Routine and Regulation

Summary. Behavioral engagement was reflected in the routinization of AI-supported learning practices, where learners translated intention into consistent and structured actions.

Habit – Integration into learning routines. AI tools became embedded in learners' everyday study practices.

> *"I found it enjoyable. The personalized feedback and quick access to additional resources kept me motivated to learn."* (P1)

> *"I enjoy using AI tools. They make the learning experience more interactive and dynamic."* (P2)

Repeated use normalized AI-supported learning behaviors, reinforcing habit formation and sustained participation in MOOCs, consistent with prior work identifying habit as a key driver of continued technology use (Venkatesh et al., 2012).

Behavioral engagement – Regulation and action. Participants described how AI supported structured learning behaviors and task completion.

> *"I now regularly use AI tools to summarize materials, check grammar, and understand concepts more quickly."* (P3)

> *"Considering that I have not since taken a MOOC due to my negative experience …"* (P5)

These findings suggest that AI appears to function as a behavioral support mechanism, guiding learners toward consistent engagement while also highlighting that negative experiences can disrupt participation, consistent with prior conceptualizations of behavioral engagement in learning contexts (Fredricks et al., 2004).

Meta-theme III: Emotional engagement – Trust and enjoyment

Summary. Emotional engagement was shaped by learners' enjoyment and evolving trust in AI, both of which influenced sustained participation in MOOCs.

Emotional engagement – Motivation and enjoyment. AI interactivity enhanced learners' motivation and sustained interest.

> *"AI tools helped me stay more engaged by giving quick responses and motivating me to continue exploring related topics."* (P4)

> *"They made it easier to engage with the material and encouraged deeper thinking."* (P6)

Emotional engagement functioned as a key mechanism sustaining voluntary participation in learning activities, consistent with prior studies on affective engagement in AI-supported learning.

Trust in AI – Conditional and reflective trust. Trust in AI was expressed as contextual and task-dependent.

> *"I generally trust AI feedback … but I am sometimes skeptical."* (P3)

> *"I always double-check the explanations, especially for complex topics."* (P1)

These findings indicate that trust develops through reflective interaction rather than blind acceptance, with learners actively verifying AI outputs as highlighted in prior research on trust in AI systems (Zawacki-Richter et al., 2019).

Cognitive–Reflective engagement. Participants also described higher-order engagement involving critical evaluation and reflective use of AI.

> *"I teach students the value of cross-referencing results … enabling them to use AI as a research assistant."* (P7)

This suggests that AI can support deeper cognitive engagement and learner agency across contexts.

Cross-cutting theme: Socio-technical context in the global south

Summary. AI-supported engagement was shaped by socio-technical conditions, including infrastructure and social influence, which acted as both enablers and constraints. This is particularly evident in developing contexts where socio-technical disparities persist (Nguyen et al., 2025; Rasheed et al., 2025).

Facilitating conditions – Contextual constraints. Infrastructural limitations influenced the consistency of AI use.

> *"There were minor technical issues such as slow internet or occasional lags …"* (P5)

These conditions help to explain the negative association of facilitating conditions observed in the structural model.

Social influence – Peer-driven adoption. Social interactions played a key role in AI adoption.

> *"Some of my classmates recommended using AI tools …"* (P1)

> *"Their recommendations influenced me to use these tools more regularly."* (P6)

These findings indicate that AI adoption is socially embedded, particularly in collectivist learning contexts, as prior MOOC adoption studies have suggested, emphasizing peer influence (Zheng et al., 2015).

Summary of qualitative insights

The qualitative findings demonstrate that AI appears to function as a cognitive, behavioral, and emotional support system in MOOCs, consistent with prior frameworks of multidimensional engagement (Fredricks et al., 2004; Wei et al., 2024). Learners perceive AI not only as a functional tool but as a learning partner that enhances understanding, supports routines, and sustains motivation. These insights provide explanatory depth for the quantitative model, particularly the central role of behavioral intention in translating AI-enabled experiences into multidimensional engagement.

DISCUSSION

This mixed-methods study advances research on AI adoption and learner engagement by integrating UTAUT2 with multidimensional engagement theory (Fredricks et al., 2004; Wei et al., 2024) in a MOOC context within a developing country, specifically Vietnam. Consistent with prior technology acceptance research (Dwivedi et al., 2021; Venkatesh et al., 2012), Behavioral Intention emerged as a central mechanism linking technological and motivational factors to learner engagement outcomes. However, this study extends existing literature by demonstrating that AI appears to function not only as a utilitarian tool but also as an epistemic and affective partner that simultaneously shapes cognitive, emotional, and behavioral engagement (Holmes et al., 2019, 2022; Khosravi et al., 2022; Zawacki-Richter et al., 2019).

The structural results indicate that Perceived Personalization ($\beta = 0.249$) is the strongest predictor of Behavioral Intention, followed closely by Hedonic Motivation ($\beta = 0.242$) and Trust in AI ($\beta = 0.173$). Notably, Perceived Personalization demonstrates the highest explanatory power among all predictors, underscoring its dominant role in shaping behavioral intention. This finding partially confirms prior UTAUT2-based studies that emphasize the importance of hedonic motivation in technology adoption (Dwivedi et al., 2021; Venkatesh et al., 2012), while extending to AI-supported learning environments more recent research that highlights the importance of personalization (Khosravi et al., 2022).

The prominence of perceived personalization further suggests that learners do not merely value AI as a convenient tool but as a system that responds to their individual needs, progress, and difficulties. In this sense, personalization appears to function as a mechanism of learning relevance, helping students feel that the technology is aligned with their own academic goals and learning pace. In this specific context, perceived personalization is more strongly associated with behavioral intention than other predictors, indicating that adaptive and personalized support may play a particularly critical role in shaping learners' intention to engage with AI-enabled MOOCs in developing country settings.

In the Vietnamese higher education context, where MOOCs are increasingly integrated into formal curricula, learners often face heterogeneous academic preparedness and rely on adaptive support to regulate their learning. Qualitative findings reinforce this result, as participants described how AI-generated recommendations and tailored feedback helped them identify knowledge gaps and adjust their learning strategies. This suggests that personalization operates as a metacognitive mechanism that enhances perceived relevance and self-regulated learning, rather than merely a system feature (Agatova & Latipova, 2025; Khosravi et al., 2022).

The strong effect of Hedonic Motivation ($\beta = 0.242$), although slightly lower than Perceived Personalization, underscores the importance of intrinsic enjoyment in AI adoption. While prior studies conceptualize hedonic motivation primarily as affective pleasure (Venkatesh et al., 2012), the present findings extend this view by demonstrating that enjoyment in AI-supported MOOCs is closely tied to cognitive validation and intellectual stimulation. Learners reported experiencing satisfaction when

AI responses confirmed or refined their own thinking, suggesting that hedonic motivation in this context is cognitively grounded rather than purely experiential, consistent with emerging research on AI-driven engagement (Li & Lin, 2025; Qu & Wu, 2024). This is consistent with prior work indicating that AI can enhance engagement by fostering interactive and intellectually stimulating learning experiences (Holmes et al., 2019, 2022). Importantly, the role of hedonic motivation in this study should not be interpreted only as enjoyment in a superficial sense. Rather, the findings indicate that enjoyment emerges when AI supports intellectual curiosity, confirms learners' reasoning, and creates a sense of cognitive stimulation. This suggests that affective responses to AI in MOOCs are closely intertwined with cognitive validation.

Trust in AI also emerged as a meaningful antecedent of behavioral intention, suggesting that learners' willingness to engage with AI-enabled MOOCs depends not only on perceived usefulness and enjoyment but also on the extent to which AI is regarded as reliable, credible, and worthy of reliance. However, the qualitative findings indicate that this trust is conditional rather than absolute, as participants frequently described verifying AI-generated responses before accepting them. This implies that trust in AI in higher education should be understood as a calibrated form of trust, in which learners balance reliance with critical evaluation. The significance of trust in AI further suggests that trust may function as a foundational enabler of deeper engagement. When learners perceive AI outputs as credible and useful, they are more likely to invest emotional and cognitive effort in interacting with the system. In this sense, trust does not merely promote adoption; it also supports the quality of subsequent engagement by reducing uncertainty and encouraging sustained interaction. In AI-supported learning environments, where learners may not fully understand how recommendations or feedback are generated, trust may reduce perceived uncertainty and increase learners' willingness to engage continuously with AI-mediated learning processes.

Effort expectancy also plays an important role by lowering the cognitive and technical barriers associated with AI use. In AI-enhanced MOOCs, learners are more likely to develop behavioral intention when they perceive the system as easy to learn, easy to navigate, and manageable within their existing study routines. This is particularly important in developing country contexts, where uneven digital familiarity may make ease of use a prerequisite for sustained adoption rather than a secondary consideration. Social influence should also be interpreted as a socially embedded driver of AI adoption. The findings suggest that learners are more likely to intend to use AI when peers, classmates, or instructors signal that such tools are useful and acceptable in academic work. In this sense, social influence not only encourages initial adoption but may also normalize AI-supported learning as a legitimate part of the academic routine.

A particularly noteworthy contribution of this study is the significant negative effect of Facilitating Conditions on Behavioral Intention ($\beta = -0.181$), which contrasts with the foundational assumption in UTAUT2 that facilitating conditions positively influence technology use (Venkatesh et al., 2012). This finding diverges from much of the existing literature, which generally conceptualizes facilitating conditions as enabling factors in technology adoption (Dwivedi et al., 2021). In contrast, the qualitative evidence in this study suggests that, in a developing country context such as Vietnam, facilitating conditions may also introduce unintended constraints under resource constraints. Participants reported fragmented institutional systems, infrastructural instability, and procedural complexity, which can create friction rather than support. This finding contributes to the literature by demonstrating that facilitating conditions are highly context-dependent and may function differently in resource-constrained environments, challenging the universality of UTAUT2 assumptions (Rasheed et al., 2025; Selwyn, 2022; Zawacki-Richter et al., 2019). Importantly, the magnitude of this negative effect is comparable to several positive predictors, highlighting its substantive theoretical and practical significance. The negative effects of facilitating conditions also warrant further theoretical attention, as they challenge the conventional assumption that such conditions always support technology adoption. In this study, facilitating conditions may have been experienced not only as the availability of support but also as indicators of institutional complexity, fragmented infrastructure, and additional procedural burdens. Thus, in resource-constrained settings, facilitating conditions may paradoxically become sources of friction rather than enablers of use.

In contrast to expectations, the effect of Habit on Behavioral Intention was only marginal ($\beta = 0.117$, $p = 0.050$), and Performance Expectancy was not statistically significant in the bootstrapping analysis. These findings partially diverge from established UTAUT2 literature, where both constructs are typically strong predictors of technology use (Dwivedi et al., 2021; Venkatesh et al., 2012). A plausible explanation is that AI use in MOOCs remains an emerging, early-stage, and exploratory practice rather than a fully routinized behavior. Qualitative insights indicate that learners use AI tools flexibly and task-dependently rather than habitually, suggesting that habit formation may require longer exposure and sustained interaction. Similarly, the potentially diminished role of performance expectancy may reflect a shift in baseline expectations, where AI is perceived as a standard support tool rather than a differentiating factor influencing adoption. This finding aligns with recent discussions on the normalization of AI in educational contexts (Holmes et al., 2019, 2022; Zawacki-Richter et al., 2019). Notably, the non-significant effect of Performance Expectancy in the bootstrapping analysis suggests that its influence may not be stable across resampling procedures, warranting cautious interpretation. The weaker and less stable effects of habit and performance expectancy may reflect the early stage of AI integration in MOOCs. For many learners, AI use appears to remain exploratory and task-specific rather than fully routinized, while its performance benefits may already be taken for granted. This suggests that as AI becomes more normalized in higher education, these relationships may change over time.

These results also confirm the mediating role of behavioral intention as the main pathway through which technological and motivational factors influence learner engagement. In other words, the model suggests that AI-related perceptions do not automatically translate into engagement; instead, they first shape learners' intention to use AI, which then drives behavioral, emotional, and cognitive engagement. The effects of behavioral intention on the three engagement dimensions suggest that AI-supported learning influences engagement in a differentiated manner. The strongest effect on emotional engagement indicates that learners' intention to use AI is first translated into affective responses such as enjoyment, motivation, and interest. This emotional activation may then facilitate behavioral participation and cognitive investment, as learners become more willing to interact with course materials, sustain effort, and engage in deeper processing. The slightly lower effects on cognitive and behavioral engagement further suggest that while intention is necessary, it may not be sufficient on its own to produce sustained learning behaviors and deep cognitive involvement without supportive pedagogical design. These findings also imply that engagement in AI-enhanced MOOCs is multidimensional rather than linear. Behavioral intention does not simply trigger usage; it appears to initiate a broader engagement process in which emotional and cognitive states are activated alongside observable learning behaviors. This supports the view that AI in higher education should be understood as shaping the quality of engagement, not only the frequency of use. This extends conventional technology acceptance perspectives by positioning behavioral intention as part of a broader engagement formation process rather than merely a predictor of system usage.

Although the R^2 value for Behavioral Intention indicates a moderate level of explanatory power, the lower R^2 values for Behavioral, Emotional, and Cognitive Engagement suggest that learner engagement is shaped by additional factors beyond the present model. This implies that variables such as self-regulation, digital literacy, prior experience with AI, and course design quality may also play important roles in explaining how AI-supported learning translates into deeper engagement outcomes.

The integration of quantitative and qualitative findings enhances the explanatory power of this study and demonstrates the explanatory value of a mixed-methods approach (Takona, 2024). While the structural model identifies statistically significant relationships, qualitative data provide contextual explanations for these patterns. For instance, the negative effect of facilitating conditions is explained through learners' experiences of infrastructural and procedural constraints, while the strong influence of personalization is supported by narratives emphasizing adaptive and responsive learning support.

This structured integration highlights how statistical relationships are shaped by socio-technical realities, particularly in developing country contexts. Specifically, each key quantitative finding is supported by qualitative evidence that explains the underlying mechanisms, thereby demonstrating the complementarity of the mixed-methods design. Overall, this study demonstrates that AI-enhanced learner engagement in MOOCs is shaped by a combination of technological, motivational, social, and contextual factors rather than by technological affordances alone. Behavioral intention emerged as the central mechanism through which perceived personalization, hedonic motivation, trust in AI, effort expectancy, social influence, and facilitating conditions influenced learner engagement. Among these predictors, perceived personalization played the strongest positive role, while facilitating conditions showed a notable negative effect, underscoring the importance of socio-technical context in shaping AI adoption. The findings further suggest that AI supports engagement not only at the behavioral level, but also through emotional and cognitive pathways, highlighting its role as both a learning tool and an epistemic partner in higher education. More broadly, the findings suggest that the effectiveness of AI in higher education MOOCs depends not only on technological sophistication but also on how AI systems align with learners' psychological needs, contextual realities, and self-regulated learning processes.

CONCLUSION

GENERAL CONCLUSION

This study examines how AI shapes learner engagement in MOOCs within a developing country context, addressing the research question of how technological, motivational, and contextual factors influence behavioral intention and multidimensional engagement. Using a mixed-methods approach grounded in UTAUT2, the findings provide both quantitative and qualitative insights into AI-enhanced learning.

The quantitative results revealed that Perceived Personalization ($\beta = 0.249$) is the strongest predictor of Behavioral Intention, followed by Hedonic Motivation ($\beta = 0.242$) and Trust in AI ($\beta = 0.173$). In contrast, Facilitating Conditions demonstrated a significant negative effect ($\beta = -0.181$), while Habit showed only a marginal effect ($p = 0.050$), and Performance Expectancy was not significant in the bootstrapping analysis. Behavioral Intention, in turn, was significantly associated with all three dimensions of engagement – behavioral, emotional, and cognitive – confirming its central mediating role.

The qualitative findings complement these results by revealing that learners perceive AI as an epistemic and affective partner that supports understanding, reflection, and motivation. Key themes include AI-driven personalization as a mechanism for metacognitive regulation, enjoyment emerging from cognitive validation rather than entertainment, and infrastructural and institutional constraints shaping engagement experiences. Together, these findings demonstrate that AI-enhanced engagement is not solely technology-driven but is co-constructed through cognitive, emotional, and socio-technical processes.

Overall, the study provides a comprehensive answer to the research question by showing that personalization, trust, and intrinsic motivation are key drivers of AI adoption, while contextual constraints in developing countries can significantly alter expected patterns of technology adoption.

PRACTICAL IMPLICATIONS

The findings provide several actionable implications for stakeholders. First, the dominant role of Perceived Personalization suggests that MOOC providers should prioritize adaptive learning systems, such as AI-driven recommendations, personalized feedback, and dynamic learning pathways. These features enhance metacognitive regulation and perceived relevance, which are critical for sustaining engagement.

Second, the strong effect of Hedonic Motivation indicates that AI tools should be designed not only for functionality but also for intrinsic engagement. Rather than focusing solely on efficiency, designers should incorporate interactive, responsive, and intellectually stimulating features that foster enjoyment through cognitive validation and exploration.

Third, the negative effect of Facilitating Conditions highlights a critical design challenge. Institutional and technical support should be carefully structured to be enabling rather than restrictive. In developing country contexts, fragmented systems, procedural complexity, and infrastructural instability can create friction that may discourage usage. Therefore, policymakers and institutions should prioritize seamless integration, low-bandwidth optimization, and user-centered system design.

Finally, for educators, AI tools can effectively support self-regulated learning and metacognition. However, learners should be guided to critically evaluate AI outputs to avoid over-reliance, ensuring that AI functions as a learning partner rather than replacing learners' cognitive effort.

Theoretical Contribution

This study contributes to the literature by extending UTAUT2 beyond its traditional focus on technology acceptance toward a motivational–experiential engagement framework. While prior studies conceptualize UTAUT2 as a model of behavioral intention driven primarily by functional and social factors (Venkatesh et al., 2012), this study reconceptualizes Behavioral Intention as a mediating mechanism that translates AI-enabled experiences into multidimensional learner engagement.

In contrast to existing research, which largely treats AI as a utilitarian tool, this study positions AI as an epistemic and affective partner that simultaneously supports cognitive, emotional, and behavioral processes. Furthermore, the finding that Perceived Personalization appears to outweigh Hedonic Motivation partially challenges traditional UTAUT2 assumptions by highlighting the central role of adaptive and context-aware learning systems in AI-supported education.

Finally, by focusing on a developing-country context, this study demonstrates that key constructs, such as Facilitating Conditions, are not universally positive but highly context-dependent. This extends prior work by emphasizing the need for socio-technical adaptation in technology acceptance models applied to educational environments in the Global South.

Limitations and Future Research

Several limitations should be acknowledged. First, the study adopts a cross-sectional design, which limits the ability to establish causal relationships among variables. Although the structural model identifies significant associations, the directionality of these relationships should be interpreted with caution. In addition, the study relies on self-reported data collected at a single point in time, which may introduce Common Method Bias, although statistical checks (e.g., Harman's single-factor test) were conducted to mitigate this concern. Second, the sample is largely homogeneous, with most participants having experience with a dominant MOOC platform (e.g., Coursera), which may limit the generalizability of the findings to other platforms or learning environments.

Third, although the qualitative component provides valuable depth, the relatively small sample size ($n = 7$) may not fully capture the diversity of learner experiences. Additionally, while qualitative insights were used to interpret quantitative findings, the selective use of participant quotations may constrain the richness and transparency of qualitative evidence. Furthermore, as the analysis followed a reflexive thematic approach, interpretations may be influenced by the researcher's subjective lens.

Future research should integrate behavioral learning analytics with self-reported measures to provide a more objective assessment of engagement. Cross-cultural studies across different developing regions would help validate the contextual nature of the findings. Longitudinal designs are also recommended to examine how AI adoption and engagement evolve. Future studies may also examine the differential effects of specific AI features (e.g., personalization, feedback, or conversational agents) on distinct dimensions of learner engagement.

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APPENDIX

APPENDIX A. MEASUREMENT ITEMS

Construct	Code	Item
Performance Expectancy (PE)	PE1	I believe using AI in MOOCs helps me learn more effectively.
	PE2	Learning with AI support improves my academic performance.
	PE3	AI helps me complete learning activities more efficiently.
	PE4	Using AI-integrated MOOCs helps me achieve my learning objectives.
Effort Expectancy (EE)	EE1	I find it easy to learn using AI-integrated MOOCs.
	EE2	I find AI features in MOOCs simple to use.
	EE3	I can quickly learn how to use AI functions in the course.
	EE4	I experience minimal difficulty when using AI-supported learning systems.

Construct	Code	Item
Social Influence (SI)	SI1	People around me encourage me to take AI-enabled MOOCs.
	SI2	My choice of AI-enabled MOOCs is influenced by friends or peers.
	SI3	Others' opinions influence my use of AI in learning.
	SI4	Instructors or academic experts recommend that I use AI in learning.
Facilitating Conditions (FC)	FC1	I have sufficient resources (e.g., computer, internet) to use AI-enabled MOOCs.
	FC2	I can easily access AI-integrated MOOC platforms.
	FC3	I receive adequate technical support when using AI systems in courses.
	FC4	I am provided with sufficient guidance on how to use AI features in learning.
Hedonic Motivation (HM)	HM1	I find learning on AI-enabled MOOCs enjoyable.
	HM2	Using AI in learning makes the experience more exciting.
	HM3	I feel mentally stimulated when AI supports my learning process.
	HM4	AI makes my learning experience more engaging.
Habit (H)	H1	I regularly use digital technologies for learning.
	H2	Learning through online platforms has become habitual for me.
	H3	Using AI to support learning feels natural to me.
	H4	Using AI is part of my regular learning routine.
Trust in AI (TA)	TA1	I trust the learning suggestions provided by AI.
	TA2	I believe AI provides recommendations that match my abilities.
	TA3	I find AI in MOOCs to be trustworthy.
	TA4	I can rely on AI to support my learning process.
Perceived Personalization (PP)	PP1	AI adapts course content to suit my learning needs.
	PP2	AI provides me with a personalized learning path.
	PP3	AI tailors lessons and resources to match my abilities.
	PP4	I feel that the course is personalized due to AI support.
Behavioral Intention (BI)	BI1	I intend to continue taking AI-enabled MOOCs in the future.
	BI2	I plan to use AI to support my learning process.
	BI3	I am willing to recommend AI-enabled MOOCs to others.
	BI4	I expect AI-supported learning to be my primary choice in the future.
Behavioral Engagement (BE)	BE1	I actively participate in course activities.
	BE2	I complete assignments fully and on time.
	BE3	I regularly use AI to support my learning.
	BE4	I actively engage in discussions or learning forums.
Emotional Engagement (EmE)	EmE1	I feel motivated when learning on AI-enabled MOOCs.
	EmE2	I feel interested in AI-recommended course content.
	EmE3	I feel emotionally connected to the online learning process.
	EmE4	AI makes me feel supported during my learning.
Cognitive Engagement (CE)	CE1	I actively explore learning content in depth.
	CE2	I reflect on how to apply what I have learned to real situations.
	CE3	AI helps me focus on the most important knowledge.
	CE4	I invest significant effort in understanding course content.

Note: All items were measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree)

APPENDIX B. INTERVIEW PROTOCOL

Note. This semi-structured interview protocol was designed to explore learners' experiences with AI-enabled features in MOOCs, aligned with the study framework (UTAUT2 and multidimensional engagement). Interviews were conducted online and lasted approximately 30–45 minutes. Participants were encouraged to provide concrete examples where possible. The questions were used flexibly, allowing for follow-up probing based on participants' responses.

Section 1: Participant Background

1. Which country are you from?
2. What is your age and academic or professional background?
3. Have you taken any MOOCs (Massive Open Online Courses)? If yes, which platforms have you used?
4. Have you used AI tools while learning in MOOCs (e.g., chatbot tutors, personalized recommendations, automated feedback)? Please describe your experience.

Section 2: Experiences with AI in MOOCs

1. Learning Support and Usefulness (Performance Expectancy)
   a. How has AI helped you understand course content or complete learning tasks?
   b. Can you describe a specific situation where AI was particularly helpful?
2. Ease of Use (Effort Expectancy)
   c. How easy or difficult was it to use AI features in MOOCs?
   d. Were there any features that you found confusing or challenging?
3. Social Influence
   e. Did anyone (e.g., peers, instructors, or colleagues) influence your decision to use AI tools?
   f. How did their opinions affect your usage?
4. Technical Conditions (Facilitating Conditions)
   g. Did you encounter any technical issues (e.g., internet connectivity, device limitations, platform performance)?
   h. How did these issues affect your learning experience with AI?
5. Enjoyment (Hedonic Motivation)
   i. Did you find using AI tools enjoyable?
   j. In what ways did AI make your learning experience more engaging or motivating?
6. Habit
   k. Do you use AI tools regularly when learning online?
   l. Has using AI become part of your usual study routine?
7. Trust in AI
   m. To what extent do you trust the content or feedback provided by AI tools?
   n. Have there been situations where you questioned or stopped trusting AI outputs?
8. Personalization
   o. Did AI tools provide personalized recommendations or learning paths?
   p. How did this personalization affect your learning experience?
9. Future Intention (Behavioral Intention)
   q. Do you intend to continue using AI tools in your future learning?
   r. What factors influence your decision?
10. Engagement (Behavioral, Emotional, Cognitive)
   s. How, if at all, did AI tools influence how actively you participated in learning activities?
   t. How, if at all, did AI affect your motivation or emotional connection to the course?
   u. How, if at all, did AI encourage deeper thinking or reflection on the course content?

Section 3: Final Reflections

1. What improvements would you suggest for integrating AI into MOOCs?
2. Is there anything else you would like to share about your experience using AI in MOOCs?

Appendix C. Bootstrapping outcomes for the standardized Direct and Indirect effects of the proposed model

	β	Bootstrapping		
		Bias-corrected 95% CI		Two-tailed significance
		Lower-Level Confidence Interval - LLCI	Upper-Level Confidence Interval - ULCI	
Standardized direct effects				
PE → BI	0.137	-0.002	0.285	0.056
EE → BI	0.115	0.023	0.190	0.006
SI → BI	0.154	0.044	0.251	0.002
FC → BI	-0.181	-0.229	-0.056	0.004
HM → BI	0.242	0.123	0.336	0.004
H → BI	0.117	-0.026	0.248	0.102
TA → BI	0.173	0.043	0.279	0.004
PP → BI	0.249	0.132	0.361	0.003
BI → BE	0.289	0.207	0.369	0.001
BI →EmE	0.341	0.252	0.427	0.002
BI →CE	0.300	0.213	0.381	0.001
Standardized indirect effects				
PE → BI → BE	0.040	0.002	0.085	0.043
EE → BI → BE	0.033	0.009	0.059	0.004
SI → BI → BE	0.045	0.013	0.077	0.002
FC → BI → BE	-0.052	-0.092	-0.016	0.003
HM → BI → BE	0.070	0.037	0.111	0.002
H → BI → BE	0.034	-0.007	0.078	0.095
TA → BI → BE	0.050	0.016	0.093	0.002
PP → BI → BE	0.072	0.038	0.114	0.001
PE → BI → EmE	0.047	***	0.105	0.047
EE → BI → EmE	0.039	0.008	0.069	0.005
SI → BI → EmE	0.053	0.015	0.095	0.002
FC → BI → EmE	-0.062	-0.110	-0.019	0.003
HM → BI → EmE	0.082	0.044	0.128	0.002
H → BI → EmE	0.040	-0.008	0.088	0.100
TA → BI → EmE	0.059	0.018	0.112	0.003
PP → BI → EmE	0.085	0.044	0.131	0.002
PE → BI → CE	0.041	***	0.095	0.047
EE → BI → CE	0.035	0.009	0.062	0.004
SI → BI → CE	0.046	0.015	0.082	0.002
FC → BI → CE	-0.054	-0.098	-0.019	0.002
HM → BI → CE	0.072	0.041	0.114	0.002
H → BI → CE	0.035	-0.008	0.075	0.092
TA → BI → CE	0.052	0.015	0.094	0.003
PP → BI → CE	0.075	0.040	0.118	0.002

Note: ***$p < 0.001$

AUTHOR

Vi Loi Truong is an Artificial Intelligence student at FPT University, Vietnam. His research focuses on artificial intelligence in education, human–AI interaction, and educational technology, with a particular emphasis on AI-driven personalization and learner engagement in higher education. He has participated in academic conferences related to STEM education, educational technology, and artificial intelligence.