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Determinants of ThaiMOOC Engagement: A Longitudinal Perspective on Adoption to Continuance

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Abstract: Massive Open Online Courses (MOOCs) have become increasingly prevalent in higher education, with the COVID-19 pandemic further accelerating their integration, particularly in developing countries. While MOOCs offered a vital solution for educational continuity during the pandemic, factors influencing students' sustained engagement with them remain understudied. This longitudinal study examines the factors influencing learners' sustained engagement with ThaiMOOC, incorporating demographic characteristics, usage log data, and key predictors of adoption and completion. Our research collected primary data from 841 university students who enrolled in ThaiMOOC as a mandatory curriculum component, using online surveys with open-ended questions and post-course usage log analysis. Logistic regression analysis indicates that adoption intention, course content, and perceived effectiveness significantly predict students' Actual Continued Usage (ACU). Moreover, gender, prior MOOC experience, and specific usage behaviors emerge as influential factors. Content analysis highlights the importance of local language support and the desire for safety during the COVID-19 pandemic. Key elements driving ACU include video design, course content, assessment, and learner-to-learner interaction.

Keywords: MOOC continued usage; adoption; completion; developing country

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1. Introduction

The COVID-19 pandemic significantly disrupted and reshaped various activities on a global scale [1]. In particular, the higher education sector faced acute challenges, requiring a rapid transition to alternative learning solutions [2–4]. Due to widespread institutional closures, millions of students were affected, leading to the largest shift to online education in history [5]. With the abrupt shift away from classrooms in many parts of the world, universities quickly shifted to virtual and digital techniques [6]. Consequently, MOOCs have emerged as the most viable alternative for universities during the COVID-19 pandemic [7–9]. Nevertheless, it is crucial to acknowledge the need for longitudinal studies that thoroughly investigate the adoption, completion, and continued usage of MOOCs in higher education during the COVID-19 pandemic, particularly in developing countries [10–12]. This study examined key factors influencing Actual Continued Usage (ACU) in ThaiMOOC, integrating adoption, completion, demographics, and usage log data. By analyzing learner trajectories across these stages, the research aimed to enhance MOOC curriculum design and support strategies for sustained engagement.

1.1. Problems in MOOC Research Context

Despite their potential to expand access to education, MOOCs suffer from persistently low adoption and completion rates, often below 10% [13–17]. Even in post-COVID-19 contexts, retention and engagement remain significant challenges [18–20]. Research identifies low motivation, difficulty understanding content, and lack of support resources as key factors contributing to dropout rates [21]. These issues raise concerns about MOOC design, effectiveness, and learner experience [22].

Given the growing significance of MOOCs in higher education, especially during the COVID-19 pandemic, identifying the factors that influence both adoption and long-term engagement is essential. Understanding what motivates learners to adopt and persist in MOOCs can provide actionable insights for improving course design, learner support, and retention strategies [13,19]. While most research focuses on MOOCs in North America and Europe, studies on developing regions remain limited, underscoring the need for context-specific investigations [18,23].

1.2. Need of the MOOC Research in Thailand Context

Prior research has investigated MOOC adoption and completion extensively, often utilizing frameworks such as TAM, UTAUT, and UTAUT2 [18–20]. Key factors influencing completion include learner characteristics, course design, and social interaction [13–17]. However, it is crucial to recognize adoption and completion as distinct stages within a learner's MOOC journey. Further research is needed to enhance the quality and management of MOOC services, particularly in response to the challenges posed by the COVID-19 pandemic [2,6,24–26].

A longitudinal research design encompassing adoption, completion, and continued usage offers a comprehensive understanding of these interrelated stages [27]. Examining these phases in isolation limits our ability to identify factors influencing the entire MOOC experience. Addressing this gap, this study introduces Actual Continued Usage (ACU) as a key dependent variable, defined as a learner's decision to enroll in a subsequent MOOC after completing their initial course on the same platform. ACU encompasses enrollment in any subsequent ThaiMOOC course, regardless of discipline, institution, or instructor, within the next academic term. To confirm continued participation, this study tracks enrollment records and first-time access to identify ACU.

Unlike cross-sectional studies, this research adopts a longitudinal approach by following the same learners across multiple phases—adoption, completion, and continued usage. By systematically collecting survey responses, open-ended feedback, and log data from the initial MOOC at multiple time points, this study tracks the same learners across different phases to analyze how early engagement behaviors predict ACU. This approach reinforces this study's longitudinal framework by capturing learner trajectories over time rather than relying on cross-sectional data.

By examining behavioral predictors across multiple phases and measuring subsequent MOOC enrollment over time, this research tracks learner engagement trajectories beyond initial adoption and completion. This multi-phase approach provides a robust longitudinal perspective on sustained MOOC participation, allowing for the identification of early indicators influencing continued engagement. To guide this investigation, this study seeks to address the following research question:

What are the key determinants of Actual Continued Usage (ACU) in MOOCs?

By addressing this question, this study aims to contribute data-driven insights into MOOC engagement, helping educational institutions and platform providers develop strategies that foster long-term learner retention and sustained participation in online learning environments.

2. Literature Review

MOOCs are designed to promote educational accessibility, offering broad access to knowledge across diverse learner groups. Recent literature reviews provide a comprehensive overview of MOOC research, illuminating key factors influencing adoption and completion [23,28–30]. While historically, adoption intention and actual usage have sometimes been conflated, evidence suggests these are distinct stages in a learner's MOOC journey. Before exploring MOOC adoption, completion, and Actual Continued Usage (ACU), this section provides an overview of MOOCs, highlighting their advantages and challenges in the context of digital learning.

2.1. Overview of MOOCs: Evolution, Benefits, and Challenges

MOOCs have transformed global education by removing traditional barriers, evolving from early distance learning models into scalable, interactive platforms such as Coursera, edX, and Udacity [23]. Initially designed to expand access to higher education, MOOCs gained renewed importance during the COVID-19 pandemic, serving as essential learning alternatives amid widespread educational disruptions [31]. Studies highlight the critical role of MOOCs in mitigating the impact of campus closures and remote learning challenges. Barak & Usher [32] discuss how MOOCs incorporated project-based learning to enhance remote instruction, while Moore & Blackmon [23] provide a systematic review of learner experiences during the pandemic. However, despite their increased adoption, MOOCs faced limitations in real-time interaction and engagement, emphasizing the need for further research on improving large-scale digital learning environments.

2.1.1. Benefits of MOOCs

MOOCs offer numerous advantages beyond online accessibility, positioning them as valuable tools for lifelong learning, career development, and educational equity. Self-paced learning enables learners to progress at individualized speeds, making MOOCs particularly beneficial for working professionals and non-traditional students who require flexible schedules [23]. Additionally, MOOCs enhance career prospects by providing industry-recognized certifications, which have gained increasing acceptance among employers, particularly in technology-driven fields [32]. Platforms such as Coursera and FutureLearn have seen substantial enrollment growth, reflecting the rising demand for online upskilling opportunities.

Beyond career benefits, MOOCs integrate active learning methodologies such as gamification, project-based learning, and interactive assessments, fostering higher engagement and knowledge retention [31]. Their collaborative features, including discussion forums and peer assessments, promote global networking, allowing students from diverse backgrounds to exchange knowledge and develop problem-solving skills. Furthermore, MOOCs bridge educational disparities, particularly in developing regions, where access to higher education remains limited [23]. By removing financial and geographic constraints, these platforms expand low-cost or free access to high-quality educational content, improving opportunities for underrepresented communities.

2.1.2. Challenges of MOOCs

Despite these advantages, MOOCs face persistent challenges related to learner engagement and completion rates. Research indicates that MOOC completion rates often remain below 10%, as learners struggle with self-regulation, motivation, and time management [16]. The asynchronous nature of MOOCs—while promoting flexibility—often results in low engagement levels due to the lack of instructor presence and real-time feedback [31]. While some platforms integrate peer discussions, many courses fail to foster meaningful student interactions, limiting collaborative learning experiences [23].

Although some MOOCs incorporate social learning elements, such as discussion forums and peer collaboration, research suggests that these tools often fail to create engaging, community-driven interactions. Learners frequently perceive them as impersonal, with low participation reducing the potential for effective collaborative learning [23]. Furthermore, the absence of structured, instructor-led discussions can lead to reduced motivation and learner isolation, further limiting engagement [31]. Technical and accessibility limitations present additional barriers, particularly in developing nations, where learners often face internet connectivity issues, limited access to digital devices, and a lack of localized language support [31]. Addressing these constraints is essential for improving MOOC retention and ensuring their long-term effectiveness. These strengths and limitations underscore the need to examine MOOC adoption and completion patterns, forming the basis for research on Actual Continued Usage (ACU).

2.2. MOOC Adoption Intention

MOOC adoption has been the subject of significant research attention [33]. Theoretical frameworks are crucial, and the Unified Theory of Acceptance and Use of Technology (UTAUT) [34], and its extension UTAUT2 [35], have been widely applied to MOOC adoption studies.

Originally designed for corporate settings, UTAUT has proven adaptable to educational contexts. Fianu et al. [36], adapting UTAUT for Saudi Arabia, highlighted the impact of Attitude and Computer Self-efficacy on behavioral intention, performance expectancy (PE), effort expectancy (EE), and attitude related to MOOC acceptance. Hu et al. [37], applying UTAUT in China, identified PE and facilitating conditions (FCs) as primary influencers of mobile technology adoption in higher education, with moderators such as gender, age, experience, and academic discipline.

Given the unique nature of e-learning systems like MOOCs, additional factors require consideration [38,39]. Extensive literature reviews emphasize diverse influences on e-learning adoption [28,33,40,41]. Consequently, UTAUT2 aligns with recommendations from prior research for studying MOOC adoption [37,42].

Beyond adoption frameworks, MOOCs provide distinct advantages that extend beyond online accessibility, making them a valuable learning tool for diverse populations. A key benefit is self-paced learning, which allows students to progress at their own speed, accommodating varied schedules and learning styles [23]. Unlike traditional classroom environments, MOOCs offer greater flexibility, particularly for adult learners and working professionals who require asynchronous learning structures to balance education with professional and personal commitments. Additionally, MOOCs support career development and professional advancement by offering industry-recognized certificates, which enhance employability [32]. Platforms such as Coursera, edX, and FutureLearn have experienced rising enrollment rates as more individuals seek upskilling and career transitions, with MOOC certifications gaining wider acceptance among employers, especially in technology-driven sectors.

In addition to accessibility and career benefits, MOOCs incorporate innovative instructional strategies that enhance engagement and knowledge retention. Many courses integrate active learning methodologies, including gamification, project-based tasks, discussion forums, and real-world case studies, fostering interactive and collaborative learning experiences [31]. Unlike traditional online courses that primarily rely on passive content delivery, MOOCs promote collaboration and global networking through discussion boards and group-based assessments, allowing learners from diverse backgrounds to exchange ideas and develop problem-solving skills. Furthermore, MOOCs help bridge educational disparities, particularly in developing regions where access to higher education is limited [23]. By eliminating financial and geographic barriers, these platforms provide low-cost or free access to high-quality educational content, ensuring that students from underserved communities can engage in higher education without traditional institutional constraints.

Despite these advantages, MOOCs face persistent challenges related to learner engagement, motivation, and course structure, all of which significantly influence completion rates. High enrollment numbers do not necessarily translate to sustained participation, as limited interaction and the need for strong self-regulation often lead to low retention rates [16]. Addressing these barriers is essential for improving long-term engagement and fostering continued participation. The following section explores MOOC completion challenges, emphasizing the factors that contribute to learner dropout rates and potential strategies for enhancing retention.

2.3. MOOC Completion

Numerous studies have sought to identify factors influencing MOOC completion in higher education [29,41,43,44]. Goopio and Cheung Goopio and Cheung [16] highlight the importance of course design, engagement, learner experience, and time management in MOOC retention. However, Liliana et al. [7] noted that much of this research focuses on general learners and typical situations, with a need for more studies specific to higher education during pandemics like COVID-19 and exploring the perspective of non-completers. Similarly, Anand Shankar Raja and Kallarakal [45] call for research examining how to enhance retention of novice MOOC learners during periods of disruption. Furthermore, a significant gap exists in our understanding of factors influencing subsequent MOOC enrollment following course completion. Investigating this area is crucial, as MOOC completion acts as a potential gateway to sustained engagement. MOOCs hold the unique potential to foster a lifelong learning mindset, empowering learners to pursue continuous education and skill development. By examining the factors that lead learners to either continue their MOOC journey or disengage after completion, we can gain valuable insights into how to optimize the MOOC experience to promote long-term participation and the realization of lifelong learning goals.

2.4. Need of MOOC's Actual Continued Usage (ACU)

MOOCs have garnered substantial attention due to their potential to democratize education by providing learners worldwide with access to high-quality educational content, irrespective of their geographic location or financial resources [46,47]. However, it is imperative to extend our examination beyond the initial stages of MOOC participation and delve into the post-course phase, which involves the analysis of continued MOOC usage. This investigation is crucial for several compelling reasons.

Firstly, MOOCs present a distinctive opportunity to promote lifelong learning [47]. Evaluating how learners engage with MOOCs after course completion offers invaluable insights into their dedication to ongoing education and skill enhancement [48]. Comprehending the factors that influence some learners to persist in using MOOCs while others do not provide the groundwork for devising strategies to cultivate a culture of continuous learning [49].

Secondly, sustained MOOC usage holds the potential to contribute significantly to sustainable learning outcomes [50]. It enables learners to solidify their acquired knowledge, apply it in practical scenarios, and remain current with evolving subject matters and trends.

Furthermore, MOOCs are often used to address educational inequalities, particularly in developing countries [51]. Evaluating their effectiveness in realizing this objective necessitates a comprehensive examination of how learners from diverse backgrounds and with varying resource constraints engage with MOOCs over an extended period [52]. This understanding can serve as a valuable guide for educators, MOOC providers, and policy makers, enabling them to answer the needs of learners within diverse educational contexts [53]. In the subsequent section, we present models designed to investigate factors identified in MOOC adoption studies through to completion, with the aim of elucidating the determinants of Actual Continued Usage (ACU).

3. The Research Model

This research seeks to comprehensively understand MOOC learner behaviors within a developing country context during the COVID-19 pandemic. Our longitudinal study focuses on university students who enrolled in and completed ThaiMOOC courses. We build upon our previous research exploring MOOC adoption and completion factors and combine this with usage log file analysis to investigate their association with learners' Actual Continued Usage (ACU). This research has the potential to provide actionable insights for optimizing MOOC design and support services, ultimately enhancing learner experiences and outcomes in the unique context of a developing country during a global health crisis.

Dependent Variable: Actual Continued Usage (ACU)

To analyze learner retention and sustained engagement, we define MOOC Actual Continued Usage (ACU) as this study's primary dependent variable, reflecting whether learners choose to enroll in another course on the platform after completing a MOOC. ACU is measured as a dichotomous variable (Y/N) based on usage log data, which enables us to track learners' real engagement behaviors within the MOOC environment. Each independent variable examined in this study is analyzed for its potential influence on ACU, providing insights into the factors that promote sustained learner participation in MOOCs. This study collects data and conducts analysis in three phases, as shown in Figure 1.

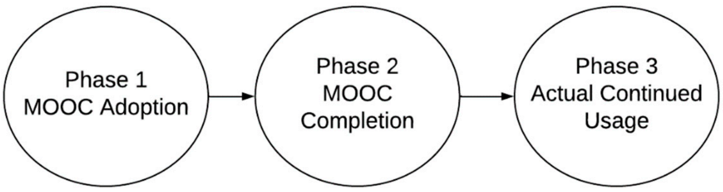

Figure 1. Research Phases.

3.1. MOOC Adoption Predictors

Building on our previous research [54], we employ an extended UTAUT2 model to investigate the factors influencing MOOC learners' adoption. This section introduces the constructs considered within our study.

Performance Expectancy (PE)

Performance expectancy, as defined by Venkatesh et al. [34], refers to the degree to which an individual believes that using a system will enhance their job performance. Within educational technology, performance expectancy is widely acknowledged as a pivotal predictor of technology adoption [37,39,55]. Considering the unique challenges of the COVID-19 pandemic, we hypothesize that:

H1: *PE is positively associated with MOOC's ACU.*

Effort Expectancy (EE)

Effort expectancy, which indicates the ease of using a technology, has been identified as a critical determinant in technology acceptance models [39,56]. The model's effectiveness in various contexts, particularly in developing countries, is yet to be fully explored [57,58]. Notably, Al-Azawei and Alowayr [59] found that in different cultural contexts, effort expectancy differently influences learners' behavioral intentions. Aligned with the technology acceptance model (TAM) proposed by Davis [60], which suggests that ease of use enhances perceived usefulness, we propose:

H2: *EE is positively associated with MOOC's ACU.*

Social Influence (SI)

Social influence, defined by Venkatesh et al. [34] as the degree to which an individual perceives the importance of others believing they should use the technology, has a noted impact on technology adoption intentions [61,62]. Empirical studies have further validated the predictive power of social influence on performance expectancy [63–65]. Therefore, we hypothesize:

H3: *SI is positively associated with MOOC's ACU.*

Facilitating Conditions (FCs)

Facilitating conditions refer to the degree to which an individual believes that organizational and technical support is available to use a system [34]. The advent of MOOCs has expanded access to open, high-quality educational resources, offering a flexible learning environment that transcends geographic and temporal barriers. However, the need for adequate facilitation to access these resources remains significant [36,37]. Thus, we propose:

H4: *FCs are positively associated with MOOC's ACU.*

Hedonic Motivation (HM)

Venkatesh et al. [35] describe hedonic motivation as the pleasure or fun derived from using technology. In the context of MOOCs, this encompasses enjoyment, engagement, and the flow of the learning experience [66]. Research consistently shows that hedonic motivation significantly influences behavioral intentions and technology use [67–69]. Thus, we hypothesize:

H5: *HM is positively associated with MOOC's ACU.*

Habit (HA)

Habit, defined as the extent to which individuals perform behaviors automatically due to learning [35], has emerged as a significant factor in technology adoption. Research findings suggest that habits formed through prior use significantly influence future technology adoption intentions [70–72]. Accordingly, we propose:

H6: *HA is positively associated with MOOC's ACU.*

Local Language Support (LLS)

The significant expansion of MOOC offerings highlights a trend towards using MOOCs as a primary learning platform [73]. However, the predominance of English language courses presents barriers for non-native speakers [74,75]. Studies indicate that local language support can substantially affect learners' adoption and continuance decisions [76].

Given the primary use of Thai in our target demographic, we include local language support as a new construct in our model and hypothesize:

H7: *Local language support (LLS) is positively associated with MOOC ACU.*

Adoption Intention (AI) and Completion

Reflecting on the combined influences of the predictors from both the MOOC adoption and completion frameworks [54,77], we integrate adoption intention as a predictor in our model. Given the strong correlation observed between course completion and continued usage, we opt to exclude the completion variable from our model. We hypothesize:

H8: *AI is positively associated with MOOC's ACU.*

3.2. MOOC Completion Predictors

In the second stage, we advance our research by proposing a self-developed model to analyze the factors influencing MOOC completion as previously outlined in [77]. The model includes the following constructs:

Assessment (AS)

Assessment strategies are crucial in any educational setting, and their importance is magnified in online environments [78]. The adoption of appropriate assessment techniques in MOOCs is imperative, particularly for ensuring engagement and completion. Deng et al. [79] emphasized the positive impact of human-graded and peer assessment strategies in enhancing learner engagement, thereby facilitating completion. Thus, we hypothesize:

H9: *AS is positively associated with MOOC's ACU.*

Course Structure (CS)

The organization of course material into structured, easily navigable segments plays a pivotal role in learners' ability to process and retain information [80,81]. ThaiMOOC courses follow a modular format, incorporating pre-recorded video lectures, text-based reading materials, and self-paced quizzes. The absence of real-time discussions, instructor-led activities, or collaborative assignments ensures that courses remain scalable and accessible to a vast number of students.

Given that ThaiMOOC courses are designed for first-year students at a large scale, the priority is to provide a consistent and structured learning experience without the complexity of real-time interaction. While interactive learning strategies may enhance engagement, they are logistically impractical in massive open courses, making passive content delivery (videos, quizzes, and reading materials) the most viable option. However, this self-guided structure may influence learner engagement and motivation, affecting their likelihood of continued MOOC participation. Therefore, we propose:

H10: *CS is positively associated with MOOC's ACU.*

Course Content (CC)

The quality of MOOC content significantly influence learner engagement, completion, and continued enrollment [82]. ThaiMOOC courses primarily rely on video-based instruction, supplemented by quizzes and reading materials, to deliver content at scale. While high-quality video production and clear instructional design enhance comprehension, previous research suggests that MOOCs with limited interactive elements may experience higher dropout rates due to reduced engagement opportunities [83,84]. Therefore, we hypothesize:

H11: *CC is positively associated with MOOC's ACU.*

Video Design (VD)

The design and structure of video content are critical in maintaining learner interest and preventing dropouts. Optimal video length and engaging design are essential for keeping learners focused and motivated. Research suggests that MOOC videos between 6 to 9 min maximize learner engagement, while longer videos (above 12 min) lead to higher dropout rates [85,86] Shorter, well-structured videos with clear explanations improve retention and course completion rates [80,87,88]. We hypothesize:

H12: *VD is positively associated with MOOC's ACU.*

Interactivity

Instructor presence and peer collaboration are widely recognized as key factors influencing learner engagement and course retention in online education. Research suggests that instructor-led discussions and personalized feedback enhance learner motivation, while peer collaboration fosters deeper engagement. However, while interaction is generally beneficial, recent studies indicate that excessive interaction requirements, such as mandatory discussion posts and peer reviews, may lead to cognitive overload and negatively impact learning outcomes [89]. Large-scale MOOCs, such as ThaiMOOC, are designed to serve a vast number of students and therefore prioritize scalability over real-time interaction. These courses rely on pre-recorded lectures and automated assessments, which, while effective for mass instruction, limit interactivity—a factor linked to lower retention rates in previous studies [23]. Despite the absence of direct instructor interaction and peer collaboration in ThaiMOOC, prior research highlights their potential impact on learner retention and continued engagement.

Although ThaiMOOC does not incorporate these elements, prior research suggests that instructor presence and peer collaboration can enhance engagement, motivation, and long-term retention in online learning environments. Therefore, this study examines their theoretical influence on ACU to determine whether they remain significant predictors of continued MOOC participation, even in a passive learning context.

H13: *Learner-to-learner interaction (LLI) is positively associated with MOOC's ACU.*

H14: *Instructor-to-learner interaction (ILI) is positively associated with MOOC's ACU.*

H15: *Instructor support (IS) is positively associated with MOOC's ACU.*

H16: *Instructor feedback (IF) is positively associated with MOOC's ACU.*

Perceived Effectiveness (PEF)

Perceived effectiveness is a critical determinant of learner satisfaction and retention. Learners who perceive the course as effective are more likely to remain engaged and complete the course requirements [90,91]. Thus:

H17: *Perceived effectiveness (PEF) is positively associated with MOOC's ACU.*

Demographic and Behavioral Usage Log File Predictors

Demographic characteristics and behavioral data from usage logs provide deep insights into learner engagement and success within MOOC platforms [92,93]. We explore how these factors influence learners' continued usage of MOOCs:

H18: *Gender significantly influences MOOC's ACU.*

H19: *Prior MOOC experience is positively associated with MOOC's ACU.*

H20: *Faculty affiliation is significantly associated with MOOC's ACU.*

H21: *Number of completed exercises is positively associated with MOOC's ACU.*

H22: *Number of watched videos is positively associated with MOOC's ACU.*

H23: *Weeks completed course is positively associated with MOOC's ACU.*

4. Research Methodology

This study employs an embedded mixed-methods design, in which quantitative analysis serves as the primary analytical framework, while qualitative insights are embedded to provide contextual depth. The quantitative component utilizes survey responses and log data to statistically examine MOOC adoption, completion, and continued engagement (ACU). The qualitative component, comprising open-ended survey responses, is used to support and explain the quantitative findings by providing insights into learner motivations and behaviors. This design ensures that statistical trends identified through logistic regression are supplemented with explanatory insights from content analysis, aligning with established mixed-methods research practices.

4.1. Survey Design

This study employed a survey instrument hosted on the Jisc Online Surveys platform (formerly Bristol Online Surveys) under the Brunel University license. The questionnaire was administered in Thai, the primary language of Thai higher education, to ensure accessibility and contextual relevance. The survey comprised three key components: MOOC adoption constructs, MOOC completion constructs, and demographic information.

The MOOC adoption constructs were adapted from the UTAUT2 model [35], incorporating local language support (LLS) items from Hakami [76]. The MOOC completion constructs were informed by Peltier et al. [94], Palmer and Holt [95], and Guo et al. [85], ensuring a comprehensive evaluation of learner engagement. Additionally, the survey collected demographic data, including gender, age, accommodation, GPA, and faculty, to contextualize the findings.

To supplement the quantitative measures, the survey included two open-ended questions designed to capture qualitative insights into learner experiences. The first question, "What are the reasons for you to decide to complete the course?", aimed to identify key motivational factors influencing course completion. The second question, "Do you have any other suggestions or comments about the course?", provided participants with the opportunity to share general feedback and recommendations for course improvement. These qualitative responses were analyzed through content analysis, offering a deeper understanding of student perspectives beyond numerical ratings.

In addition to survey responses, usage log data from the ThaiMOOC backend system were collected to examine actual learner behaviors. The log data included the proportion of videos watched, the proportion of exercises completed, the proportion of the course period completed, and Actual Continued Usage (ACU). These behavioral metrics provided a comprehensive view of learner engagement, complementing the survey-based findings.

4.2. Sampling

A convenience sample was drawn from first-year students at a public university in Nakhon Si Thammarat, Thailand. A total of 2676 students were eligible to participate, of whom 1512 voluntarily responded, and the final valid dataset comprised 841 participants. Participation in this study was entirely voluntary, and students were informed that their responses would remain confidential. Informed consent was obtained before data collection, and students had the option to withdraw at any stage without any academic consequences.

While students were given the opportunity to enroll in ThaiMOOC courses as part of their General Education (GE) curriculum, this was not a mandatory requirement for graduation. Instead, students could choose between face-to-face (traditional teaching) and ThaiMOOC-based learning, ensuring that participation in MOOCs was an alternative learning pathway rather than an institutional obligation.

The final study sample of 841 participants was drawn from the 1512 students who voluntarily responded to the survey, representing 56.5% of those eligible to participate. A comparison of study participants with the broader ThaiMOOC user base indicates that the sample includes learners from diverse academic backgrounds, encompassing both students with and without prior MOOC experience. This diversity enhances the generalizability of findings by capturing a broad spectrum of engagement patterns and motivations within ThaiMOOC.

While the voluntary nature of this study limited control over demographic distribution, the sample provides a representative cross-section of first-year university students engaging with ThaiMOOC. The inclusion of students with different learning preferences—those opting for MOOCs and those preferring face-to-face instruction—ensures a balanced perspective on adoption, completion, and continued usage (ACU).

4.3. The Procedure

Ethical research practices were paramount in this study. Ethics approval was obtained from Brunel University London, ensuring compliance with institutional research guidelines. Data collection took place in the university's computer laboratory, where students received a detailed briefing on the research project. The briefing emphasized the voluntary nature of participation across both phases and the absence of incentives. Informed consent was obtained before data collection, and students were informed of their right to withdraw at any stage without academic consequences.

While this ethical approach ensured transparency and adherence to research standards, it may have introduced self-selection bias, as highly motivated learners were more likely to participate, potentially influencing this study's findings. Future research should consider structured recruitment strategies, such as quota sampling or targeted outreach, to enhance participant diversity and mitigate selection bias.

The data collection process spanned three months. MOOC adoption questionnaires were administered at the start of the term, followed by MOOC completion questionnaires at the end. Open-ended questions were incorporated in both phases to capture qualitative insights into learner experiences. Additionally, usage log files from the ThaiMOOC backend system were analyzed to assess ACU. ACU was operationalized as a binary variable (Yes/No), indicating whether participants enrolled in another ThaiMOOC course in the following academic term. This measure provided a longitudinal perspective on learner engagement and sustained MOOC participation. (For detailed descriptions of all variables included in the questionnaire, please refer to Appendix A, Tables A1 and A2.)

4.4. Data Screening

To ensure data quality, we focused exclusively on students engaged throughout the multi-phase study. Initial enrollment in ThaiMOOC was 2676, with 1512 students (56.5%) volunteering to participate. We received 1384 (92%) responses in phase 1 and 1152 (85.65%) in phase 2. Data screening involved:

- Removing 23 rows due to incomplete/incorrect information.
- Eliminating 86 non-engaged responses (identical answers across items).
- Removing 6 outliers (over-age data).

This yielded a final dataset of 841 questionnaires with accompanying open-ended responses, suitable for mixed-methods analysis. A detailed overview of this process is provided in Figure 2.

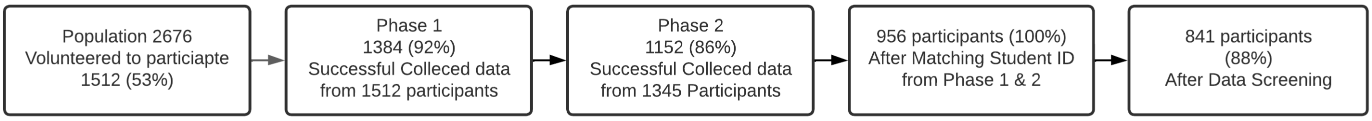

Figure 2. Data Collection Processes.

4.5. Data Analysis Method

This study employs a mixed-methods approach, integrating quantitative and qualitative methods to examine MOOC adoption, completion, and continued engagement (ACU). The combination of survey responses, open-ended qualitative feedback, and student usage log files provides a comprehensive analysis of learner behavior, capturing both self-reported motivations and behavioral indicators of sustained MOOC participation.

For the quantitative component, logistic regression was selected as the primary analytical technique to examine the determinants of continued MOOC usage (ACU). This method is particularly well suited for analyzing binary outcomes, making it appropriate for predicting whether students continued using ThaiMOOC (ACU: Yes/No) [96]. Before conducting the regression analysis, key statistical assumptions were assessed to ensure methodological rigor. Multicollinearity was tested using Variance Inflation Factor (VIF) diagnostics, confirming that all predictor variables were within acceptable thresholds (VIF < 5), thereby ensuring the absence of multicollinearity. Additionally, the dataset met the fundamental assumptions required for logistic regression, including adequate sample size, independence of observations, and a binary dependent variable. The appropriateness of parametric statistical tests was further verified by assessing the normality of key log data variables such as video completion rates and exercise completion.

For the qualitative component, content analysis was employed to systematically examine open-ended responses, allowing for a deeper exploration of learner motivations and experiences [97]. Two independent researchers performed category-based coding using a structured framework, identifying recurring themes related to learner engagement, course completion, and perceived barriers. To ensure coding consistency, iterative discussions were conducted, and discrepancies were resolved through consensus. While an inter-coder reliability test was not conducted, this collaborative approach aligns with established qualitative research methodologies, which emphasize iterative refinement of coding frameworks to ensure reliability. Given that many responses contained multiple perspectives, a multi-coding approach was applied, allowing responses to be assigned to more than one thematic category. This ensured a holistic representation of student feedback, resulting in total proportions exceeding 100%.

To further enhance data transparency, student quotes are anonymized using a coding system that provides demographic insights while preserving confidentiality. Each quote is labeled with a participant identifier (e.g., S12, D15), where 'S' denotes Science faculty students and 'D' represents Social Science faculty students. The accompanying numerical code indicates an anonymized participant ID, while 'C' (Completer) and 'NC' (Non-Completer) are used where relevant to distinguish students based on course completion status.

To ensure a comprehensive interpretation of learner engagement within ThaiMOOC, the quantitative and qualitative findings were integrated. Logistic regression quantified the statistical relationships between key predictors and ACU, while content analysis provided deeper insight into student perspectives and motivations, thereby complementing the numerical findings with rich qualitative narratives.

Additionally, student usage log files were analyzed to capture learning progression and behavioral trends within ThaiMOOC courses. Behavioral metrics—including video completion rates, exercise completion, and ACU—were standardized and incorporated as independent variables in the logistic regression model. Given the importance of ensuring accurate model estimation, parametric tests were applied where appropriate, and assumptions were verified before conducting analyses. This integration of log data and self-reported survey responses provides a nuanced, data-driven perspective on learner engagement, reinforcing the validity of this study's findings.

5. Result

This study follows a longitudinal design with three sequential phases: (1) initial MOOC enrollment (adoption), (2) completion of the initial course, and (3) analysis of Actual Continued Usage (ACU). All findings in this section are structured according to these three phases to maintain consistency with the study framework.

5.1. Descriptive

Table 1 presents participant demographic information, which is relevant for understanding sample composition and its potential influence on MOOC engagement and ACU outcomes. Since demographic factors (e.g., prior MOOC experience and faculty) are considered independent predictors in the analysis, we report them in the Results section rather than the Methods section to maintain analytical continuity.

Table 1. Demographic Information.

Demographic	Level	Number	Proportion (%)
Gender	Male	220	26
	Female	621	74
Living place	Campus	137	16
	Live with Parent	684	81
	Private Rental	20	3
High school grade	2.00–2.50	31	4
	2.51–3.00	206	24
	3.01–3.50	345	41
	3.51–4.00	259	31
Faculty	Science	709	84
	Social Science	132	16
MOOC experience	Yes	243	29
	No	598	71

A significant gender imbalance is evident, with females comprising 74% of the sample and males representing only 26%. Participants were primarily enrolled in Science faculties (84%), with a smaller representation from Social Science faculties (16%). Most participants (81%) resided with their parents, while 16% lived on campus and 3% in private rental accommodation. Regarding prior MOOC experience, 71% of participants indicated no previous exposure, while 29% had used other MOOC platforms.

Because participation was voluntary, the sample distribution was not entirely balanced. It is important to acknowledge the potential influence of these demographic characteristics, particularly the gender imbalance, when interpreting this study's findings, especially in relation to continued MOOC engagement (ACU).

5.2. MOOC Learner Completion

Usage log analysis revealed that 780 participants (93%) achieved a final assessment score exceeding 50%, thereby earning official course completion credentials. Of these completers, 193 (25%) were male and 587 (75%) were female. Conversely, 61 participants (7%) did not complete the course, with 34 (56%) male and 27 (44%) female. Table 2 presents the distribution of exercises completed, content watched/read, and course period completed. The proportions of exercises completed and content viewed exhibited skewed left distributions. This suggests that learners who completed more than half of the exercises and viewed more than half of the course content were significantly more likely to succeed.

Table 2. Learner Completion (usage log files).

Detail	Measurement	Frequency	Proportion (%)
Proportion of exercise complete			
	All (80–100%)	331	39
	Most (60–79%)	13	1
	Around Half (40–59%)	309	37
	Few (20–39%)	183	22
	Rarely (0–19%)	5	1
Proportion of content watched/read			
	All (80–100%)	96	11
	Most (60–79%)	338	40
	Around Half (40–59%)	223	27
	Few (20–39%)	142	17
	Rarely (0–19%)	42	5
Proportion of course period complete			
	First few weeks (0–2)	134	16
	Towards the middle (3–6)	240	29
	Passed middle/before the end (7–10)	305	36
	Towards to the End (11–12)	101	12
	Not Completed	61	7

The distribution of course period completion was normal, indicating that participants who reached the halfway point of the course tended to persist until completion. These findings highlight the importance of sustained learner effort throughout the MOOC experience. The following results correspond to phase 2 (MOOC completion) of the longitudinal study. As reported earlier, all participants were tracked across three phases, including those who did not complete their initial MOOC.

5.3. Demographic Effects on Learner Completion and Continued Usage

Completion: Chi-square analysis revealed a significant effect of gender on course completion ($\chi2 = 11.2$, df = 1, $p < 0.001$). Female students exhibited a higher completion rate (94.5%) than male students (87.7%). Prior MOOC experience ($\chi2 = 0.593$, df = 1, $p = 0.441$) and faculty ($\chi2 = 0.272$, df = 1, $p = 0.602$) did not significantly influence completion rates.

Actual Continued Usage: Gender also demonstrated a significant effect on continued MOOC usage in the subsequent term ($\chi2 = 22.1$, df = 1, $p = 0.001$), with female students (84.5%) choosing to continue more frequently than male students (70%). Prior MOOC experience played a significant role ($\chi2 = 7.10$, df = 1, $p = 0.008$), with those having previous experience (86.4%) exhibiting a higher likelihood of continued usage than those without prior exposure (78.4%). Faculty affiliation ($\chi2 = 0.0105$, df = 1, $p = 0.918$) did not significantly impact continued usage decisions. Table 3 presents these findings.

Table 3. Completion and Actual Continued Usage Information.

Detail	Categories	Number	Proportion (%)
Completed Course	*Completed Course*	780	93
	Male	193	25
	Female	587	75
	Did Not Complete Course	61	7
	Male	34	56
	Female	27	44
	Completed Course	780	93
	MOOC Experience	228	29
	No Experience	552	71
	Did Not Complete Course	61	7
	MOOC Experience	15	25
	No Experience	46	75
	Completed Course	780	93
	Science	659	84
	Social Science	121	16
	Did Not Complete Course	61	7
	Science	50	82
	Social Science	11	18
Actual Continued Usage	*Enrolled Next Course*	679	81
	Male	154	23
	Female	525	77
	No Longer Enrolled	162	19
	Male	66	41
	Female	96	59
	Enrolled Next Course *MOOC*	679	81
	Experience	210	31
	No Experience	469	69
	No Longer Enrolled	162	19
	MOOC Experience	33	20
	No Experience	129	80
	Enrolled Next Course	679	81
	Science	572	84
	Social Science	107	16
	No Longer Enrolled	162	21
	Science	137	85
	Social Science	25	15

5.4. Reliability and Validity

To assess the reliability and validity of the constructs used in this study, we employed several established psychometric measures. The internal consistency of our scales was assessed using both Cronbach's alpha and composite reliability (CR). As recommended by Rust and Cooil [98], a Cronbach's alpha of 0.70 was used as the threshold for acceptable reliability. All scales in both the MOOC adoption (Table 4) and MOOC completion (Table 5) phases exceeded this criterion. The composite reliability values ranged from 0.879 to 0.913 for the adoption phase and from 0.859 to 0.931 for the completion phase, further supporting the internal consistency of our measures [99].

Table 4. Convergent Validity, Loading and Reliability of MOOC Adoption.

Items	Loading	Cronbach's Alpha	AVE	Composite Reliability
Performance Expectancy		0.913	0.723	0.912
PE1	0.849			
PE2	0.843			
PE3	0.889			
PE4	0.818			
Effort Expectancy (EE)		0.906	0.705	0.905
EE1	0.829			
EE2	0.827			
EE3	0.858			
EE4	0.844			
Social Influence (SI)		0.901	0.646	0.879
SI1	0.850			
SI2	0.854			
SI3	0.747			
SI4	0.759			
Facilitating Conditions (FCs)		0.900	0.706	0.906
FC1	0.872			
FC2	0.864			
FC3	0.824			
FC4	0.800			
Hedonistic Motivation (HM)		0.900	0.778	0.913
HM1	0.882			
HM2	0.873			
HM3	0.891			
Habit (HA)		0.909	0.692	0.900
HA1	0.775			
HA2	0.911			
HA3	0.827			
HA4	0.809			
Local Language Support (LL)		0.914	0.660	0.906
LL1	0.833			
LL2	0.832			
LL3	0.827			
LL4	0.707			

Table 4. *Cont.*

Items	Loading	Cronbach's Alpha	AVE	Composite Reliability
Adopting Intention (AI)		0.896	0.742	0.896
AI1	0.831			
AI2	0.851			
AI3	0.900			

Table 5. Convergent Validity, Loading and Reliability of MOOC Completion.

Items	Loading	Cronbach's Alpha	AVE	Composite Reliability
Instructor-to-Learner Interaction		0.888	0.666	0.888
ILI1	0.774			
ILI2	0.818			
ILI3	0.834			
ILI4	0.836			
Instructor Support		0.917	0.668	0.910
IS1	0.816			
IS2	0.821			
IS3	0.819			
IS4	0.799			
IS5	0.831			
Instructor Feedback		0.906	0.709	0.907
IF1	0.861			
IF2	0.803			
IF3	0.868			
IF4	0.835			
Learner-to-Learner Interaction		0.892	0.620	0.890
LLI1	0.671			
LLI2	0.793			
LLI3	0.803			
LLI4	0.812			
LLI5	0.848			
Course Content		0.907	0.665	0.908
CC1	0.823			
CC2	0.772			
CC3	0.848			
CC4	0.826			
CC5	0.805			
Course Structure		0.886	0.724	0.887
CS1	0.851			
CS2	0.845			
CS3	0.856			
Assessment		0.849	0.671	0.859
AS1	0.807			
AS2	0.884			
AS3	0.762			

Table 5. *Cont.*

Items	Loading	Cronbach's Alpha	AVE	Composite Reliability
Video Design		0.906	0.663	0.908
VD1	0.759			
VD2	0.796			
VD3	0.837			
VD4	0.846			
VD5	0.830			
Perceived Effectiveness		0.895	0.737	0.894
PE1	0.849			
PE2	0.870			
PE3	0.856			

Convergent validity, which refers to the degree to which items within a scale measure the same underlying construct, was evaluated using Average Variance Extracted (AVE). As recommended by Fornell and Larcker [100], an AVE of 0.50 or higher was considered adequate. Our results, shown in Tables 4 and 5, demonstrate that all scales met this criterion, confirming the convergent validity of our measures.

The rigorous reliability and validity assessment confirms the psychometric soundness of this study's scales. High internal consistency (Cronbach's alpha and CR) ensures each scale measures a single construct, while satisfactory AVE values establish construct distinctiveness. These findings support the validity of subsequent analyses.

5.5. Logistic Regression

5.5.1. Model Evaluation

Goodness of Fit: To assess the logistic regression model's adequacy, we employed the Hosmer and Lemeshow test [101]. The obtained chi-square statistic was 2.731 (8 degrees of freedom), with a non-significant p-value of 0.950 (>0.05). This indicates a good model fit, as there is no statistically significant discrepancy between the model's predictions and the observed data [102].

Omnibus Test: The Omnibus Test of Model Coefficients yielded a significant chi-square statistic of 473.875 (df = 23, p = 0.000). This result demonstrates that our model's independent variables hold significant predictive power in explaining MOOC continued usage (our dependent variable). Nagelkerke's R2 suggests that the model accounts for approximately 63.7% of the variance in the outcome.

5.5.2. Performance of a Classification Model

Table 6 offers insights into our model's accuracy for predicting continued MOOC usage (a binary classification). Overall, the model achieved a high classification accuracy of 91.44%. It correctly predicted 97.05% of cases where participants intended to continue MOOC use, and 67.90% of cases where they did not.

Table 6. Classification Table.

		Predicted		Correct
		0	**1**	
Actual	No	110	52	67.90%
Continued	Yes	20	659	97.05%
Usage	Total			91.44%

The Positive Predictive Value (PPV), which addresses the likelihood that those predicted to continue will actually do so, was 92.68%. This indicates strong model performance in identifying those likely to engage in continued usage. The Negative Predictive Value (NPV), reflecting the likelihood that those predicted not to continue will indeed discontinue use, was 84.61%. This suggests the model is also effective in identifying those less likely to persist. These findings underscore the potential practical value of our model in identifying learners who may benefit from additional support to encourage continued MOOC engagement.

5.5.3. The Odds Ratios and Tests of Hypotheses

Logistic regression analysis revealed significant effects of several predictors on learners' likelihood of continued ThaiMOOC usage. Table 7 provides coefficients (B), standard errors, z-values, *p*-values, odds ratios, and 95% confidence intervals for all predictors. Demographics: Gender emerged as a significant factor, with male students 49% less likely than females to continue MOOC use ($p = 0.037$). Prior MOOC experience substantially increased the odds of continued usage (odds ratio = 2.42, $p = 0.011$). This highlights the importance of early positive experiences in fostering sustained engagement. Learner Behaviors: Completion of exercises and videos strongly predicted continued usage ($p < 0.001$ for both). Each additional exercise completed increased the odds by a factor of 1.6, and each additional video watched by a factor of 1.29. Weeks of course completion also had a notable cumulative effect, increasing the odds by a factor of 1.34 for each additional week ($p < 0.001$). Adoption Predictors: Adoption intention was the only significant predictor from the MOOC adoption model. Each unit increase in adoption intention led to an impressive 8.09 times greater odds of continued usage ($p < 0.001$). This underscores the importance of factors that shape learners' initial motivation and commitment. Completion Predictors: Course content and perceived effectiveness were highly influential. Negative perceptions of content decreased odds of continuation (odds ratio = 0.28, $p = 0.004$), while positive perceptions had a substantial positive effect (odds ratio = 2.92, $p = 0.001$). These findings emphasize the need for high-quality content and instructional design that demonstrates tangible value to learners.

Table 7. All Predictors' Odds Ratios with 95% Confidence Intervals.

	Coefficient B	Standard Error	z	*p*	Odds Ratio	95% Conf. Interval	Hypotheses Result
MOOC Adoption Predictors							
Performance expectancy (H1)	0.5	0.29	1.71	0.088	1.65	0.93–2.93	Rejected
Effort expectancy (H2)	−0.29	0.3	0.96	0.337	0.75	0.41–1.35	Rejected
Social influence (H3)	−0.2	0.33	0.6	0.547	0.82	0.43–1.56	Rejected
Facilitating conditions (H4)	0.21	0.33	0.63	0.528	1.23	0.65–2.34	Rejected
Hedonic Motivation (H5)	−0.2	0.91	0.22	0.824	0.82	0.14–4.83	Rejected
Habit (H6)	−0.15	1.11	0.13	0.895	0.86	0.1–7.65	Rejected
Local Language (H7)	−0.18	0.37	0.48	0.633	0.84	0.4–1.73	Rejected
Adoption Intention (H8)	2.09	0.3	6.91	<0.001	8.09	4.47–14.64	Not Rejected
MOOC Completion Predictors							
Assessment (H9)	−0.03	0.28	0.1	0.924	0.97	0.56–1.7	Rejected
Course Structure (H10)	−0.21	0.31	0.66	0.51	0.81	0.44–1.5	Rejected
Course Content (H11)	−1.26	0.43	2.91	0.004	0.28	0.12–0.66	Not Rejected
Video Design (H12)	0.5	0.36	1.4	0.161	1.66	0.82–3.35	Rejected
Learner-to-Learner Interaction (H13)	−0.05	0.34	0.16	0.874	0.95	0.49–1.84	Rejected
Instructor-to-Learner Interaction (H14)	−0.02	0.37	0.05	0.959	0.98	0.48–2.02	Rejected
Instructor Support (H15)	0.24	0.4	0.61	0.543	1.27	0.59–2.77	Rejected
Instructor Feedback (H16)	−0.2	0.26	0.8	0.426	0.81	0.49–1.35	Rejected
Perceived Effectiveness (H17)	1.07	0.33	3.29	0.001	2.92	1.54–5.52	Not Rejected

Table 7. *Cont.*

	Coefficient B	Standard Error	z	p	Odds Ratio	95% Conf. Interval	Hypotheses Result
Demographic and Usage Log File							
Gender (Male) (H18)	−0.67	0.32	2.08	0.037	0.51	0.28–0.96	Not Rejected
Prior MOOC Experience (Y) (H19)	0.88	0.35	2.54	0.011	2.42	1.22–4.78	Not Rejected
Faculty (Social Science) (H20)	0.44	0.42	1.04	0.297	1.55	0.68–3.5	Rejected
Completed exercises (H21)	0.47	0.06	8.07	<0.001	1.6	1.43–1.80	Not Rejected
Watched videos (H22)	0.26	0.05	4.75	<0.001	1.29	1.16–1.44	Not Rejected
Weeks completed the course (H23)	0.29	0.05	6.24	<0.001	1.34	1.22–1.47	Not Rejected

Several MOOC adoption and completion predictors were not statistically significant. This shows that other factors may be more important in MOOC use than previously thought. Implications: This analysis improves MOOC design and learner support. Male students and first-time MOOC participants may benefit from targeted interventions. Course content, perceived effectiveness, and adoption intention strongly influence initial interest and commitment, emphasizing the need for well-designed, relevant courses and tactics. These findings can help optimize MOOCs for lifetime learning.

5.6. Open-Text Responses

5.6.1. Open-Text Responses: The MOOC Adoption Model

The collection of open-ended textual responses spanned both the MOOC adoption and completion stages of this study. To systematically analyze these responses, content analysis was employed, allowing us to identify implicit meanings and recurring themes within learner feedback. The responses were carefully coded into distinct categories, providing a deeper understanding of learner motivations and experiences.

To complement the quantitative findings, open-ended responses were categorized into multiple themes, acknowledging that some responses contained more than one idea. As a result, responses were multi-coded, leading to a total proportion exceeding 100%. This multi-coding approach has been explicitly detailed in Section 4.5 (Data Analysis Method) to ensure transparency in the categorization process.

The initial analysis focused on open-ended responses from the MOOC adoption phase. Among the 841 participants, a significant 81% (n = 678) provided feedback. Of these responses, 94% (n = 637) were positive, clustering into two primary categories. The first category reflects strong enthusiasm for local language support (LLS), with 62% (n = 395) of respondents expressing a preference for ThaiMOOC due to its Thai language offerings. This sentiment is exemplified by student feedback, including:

> *"I found the course to be easier to comprehend."* (S21)

> *"Thai sound made explanation of case studies clearer and applicable!"* (D14)

> *"It is quite intriguing to enroll in online courses that offer content in our local language."* (S35)

> *"The university should make the Thai language available for all new courses."* (D27)

Additionally, the native language support encouraged students to enroll in the course because they felt confident in their ability to comprehend the material. In addition, the majority of students believed that reviewing course material with local language support prior to an examination was convenient. A minority of respondents, however, would like to see multiple language support as an option for all course content. They cited the opportunity to enhance their language skills and the possibility of a promising career path in the future.

The second category is "Stay safe from COVID-19." A significant 38% (n = 242) of participants who adopted ThaiMOOC explicitly cited feeling safer from COVID-19 infection as a key motivator. They valued ThaiMOOC's flexibility as it allowed them to continue their studies while minimizing health risks associated with crowded, traditional classrooms. This is exemplified by student comments such as

"I was able to finish the enrolled course even though I got COVID-19 during the term." (S12)

"I feel secure studying from home during the COVID-19 pandemic." (D08)

"My parents are relieved I am not required to attend class in person." (S30)

In contrast, 6% (n = 41) of responses expressed negative feedback, primarily concerning issues related to facilitating conditions (FCs). This feedback highlighted challenges stemming from ThaiMOOC's platform compatibility across different devices, the quality and stability of learners' internet connections, and varying levels of computer literacy. These concerns were illustrated by student comments such as

"Getting an answer from the online forum took too long." (D18)

"My internet kept disconnecting as I attempted to take the online test." (S26)

"I had no idea how to complete the ThaiMOOC course assignment." (S31)

"The software on my tablet was not compatible with ThaiMOOC." (D10)

An interesting observation emerged from the analysis of open-ended responses: a subset of students demonstrated positive attitudes towards performance expectancy (PE), indicating a belief that MOOCs could enhance their skills and knowledge. Given that PE is traditionally considered a determinant of initial MOOC adoption, its presence among students who had already adopted ThaiMOOC was unexpected. This finding suggests that even after engaging with the platform, some learners continue to perceive MOOCs as beneficial for their academic and professional development, potentially influencing their future engagement intentions. Notably, 5% of adopters (n = 31) did not provide open-ended feedback.

5.6.2. Open-Text Responses of MOOC Completion

In our analysis of open-ended responses of MOOC completion, a significant 87% (n = 730) of the 841 students provided feedback. Responses were largely divided into two groups: those from MOOC completers (94%, n = 686) and those from non-completers (6%, n = 44). The first group, video design (VD) (52%, n = 357), emerged as a dominant factor among MOOC completers. Many students emphasized that well-designed videos played a critical role in fostering comprehension, motivation, and course completion. Participants highlighted that visually engaging content, concise explanations, and the ability to review videos for exam preparation were particularly valuable. Some responses illustrated this perspective:

"The 2D & 3D graphics in the video enable more memorable and understandable content." (S11, C)

"I anticipate that more programs will provide similar quality video content." (D22, C)

"It felt like I was watching a YouTube channel with rich and well-structured video content." (S17, C)

"I prefer concise and understandable video content that conveys the chapter's main idea in a few minutes." (D30, C)

Students also cited VD as a factor in facilitating faster comprehension of complex concepts, and many found reviewing videos to be an efficient exam preparation strategy.

However, a minority of respondents expressed a preference for face-to-face instruction, emphasizing the importance of real-time interaction with peers and instructors for enhancing comprehension and engagement. This finding aligns with prior research indicating that face-to-face learning environments foster deeper interaction, immediate feedback, and collaborative learning experiences, which are often difficult to replicate in asynchronous MOOCs [103]. While MOOCs offer flexibility and accessibility, the absence of direct communication may present challenges for learners who rely on synchronous discussions to reinforce their understanding and maintain motivation.

The second major theme, course content (CC) (17%, n = 116), was frequently cited by MOOC completers as a critical factor influencing their course completion. Participants noted that the content equipped them with practical skills and knowledge applicable to their professional goals, reinforcing the value of MOOCs in bridging theory and real-world application. Many students also appreciated the provision of supplementary resources that enhanced their confidence in applying what they had learned. Key student comments include

> *"I like the content that provides current and practical usage in real business."* (D05, C)

> *"I gained skills and knowledge which improved my confidence to step into the employment market."* (S20, C)

The third theme, assessment (AS) (13%, n = 95), highlighted the role of quizzes and structured assessments in confirming comprehension and identifying content misconceptions. Students reported that being actively engaged in assessments improved their performance on the final exam and reinforced their understanding of key concepts. Some responses included

> *"The assessment is an ideal preparation tool for the final exam."* (S15, C)

> *"I got more knowledgeable after completing each section's assessment."* (D28, C)

> *"Assessment enhanced my understanding of a specific topic."* (S36, C)

The fourth theme, learner-to-learner interaction (LLI) 9% (n = 68), reflected how ThaiMOOC's online forum became an integral component of student engagement. Many students reported that the forum was a useful tool for finding answers to course-related questions, sharing insights with peers, and fostering a sense of competition. Several students noted that the forum provided a more comfortable alternative to asking questions in a traditional classroom setting. Key student responses included

> *"I prefer to pose inquiries through online forums rather than directly inquire in the classroom."* (S29, C)

> *"The online forum was useful for inquiring and sharing specific solutions with other students."* (D08, C)

> *"The online forum encourages competition between me and my friends, who will complete the lesson faster and with a higher score."* (S14, C)

Interestingly, several students admitted that they were too embarrassed to raise questions in class, which made the online discussion forum a more attractive alternative for seeking clarification [104]. Additionally, some respondents noted that the diverse perspectives shared in the forum enriched their understanding of course content [105]. The final category includes No Comment (3%, n = 19), where students provided "-" or "null" responses, indicating that they had no specific feedback or suggestions regarding their MOOC experience.

In contrast, 75.41% (n = 46) of the 61 non-completers responses demonstrated oppositional viewpoints to ThaiMOOC. Instructor-to-learner interaction (ILI), instructor support

(IS), and instructor feedback (IF) caused significant problems for the majority of learners who fell out of the course. Regarding the ILI, students suggested that ThaiMOOC enhance its support for online instructor–student interaction. As a number of learner queries required prompt responses from instructors, learners lost motivation when they must wait more than a day for the response. Moreover, several responses suggested that ThaiMOOC should enhance responding time for online discussion groups. Instructors should promptly assist students by responding to their questions while exchanging information on the discussion board, which will increase their engagement in building study skills. The non-completer, in the meantime, expects Infrastructure Support, particularly when students encounter issues with obstacles. They require assistance from the instructor or teaching teams to resolve technical issues, how-to guides, etc. Additionally, the IF should be included in the real-time online discussion, allowing students to inquire about and comprehend more instructor feedback. For instance

"It took three days to get a response from the instructor." (D07, NC)

"I required assistance from the instructional staff. I had no idea where to begin." (S13, NC)

"Instructors did not provide sufficient assistance to meet the needs of students." (D16, NC)

It is noteworthy to observe that several non-completers have provided positive feedback that reflect on perceived effectiveness. Even if they did not complete the course, they acknowledged the benefits of ThaiMOOC as a suitable response to the COVID-19 outbreak. They recognized the online learning format and planned to enroll intentionally. As an example, a non-completer mentioned:

"It was more convenient to study at home during the COVID-19 pandemic." (S10, NC)

"In my opinion, ThaiMOOC is a viable option for students during the COVID-19." (D09, NC)

"I was afraid of university suspension during COVID-19, but ThaiMOOC provided the opportunity to continue studying with no transit problems." (S18, NC)

6. Discussion

This study aimed to answer the research question: "What are the key determinants of Actual Continued Usage (ACU) in MOOCs?" The findings confirm that adoption intention (AI), course content (CC), and perceived effectiveness (PEF) are the most influential predictors of sustained engagement with ThaiMOOC. AI emerged as the strongest determinant, reinforcing that strong initial motivation and a positive attitude towards MOOCs drive long-term participation. Learners with higher AI were significantly more likely to continue enrolling in ThaiMOOC, suggesting that MOOC providers should focus on strengthening AI through structured onboarding, motivational reinforcement, and engagement-driven course design.

Key Findings

This study employed a multi-phase empirical approach involving 841 higher education learners in Thailand, capturing both MOOC completers and non-completers. The inclusion of non-completers is particularly significant, as many provided valuable feedback in open-ended responses, which were analyzed in Section 5.6.2 (Open-Text Responses of MOOC Completion). This ensures a more comprehensive representation of learner experiences, offering insights into both successful completion and the challenges faced by those who discontinued their MOOC engagement.

Figure 3 presents an integrated conceptual framework illustrating the key factors influencing MOOC adoption, completion, and Actual Continued Usage (ACU). This model synthesizes this study's empirical findings, mapping the relationships between adoption intention, course-related factors, learner engagement, and sustained participation in ThaiMOOC.

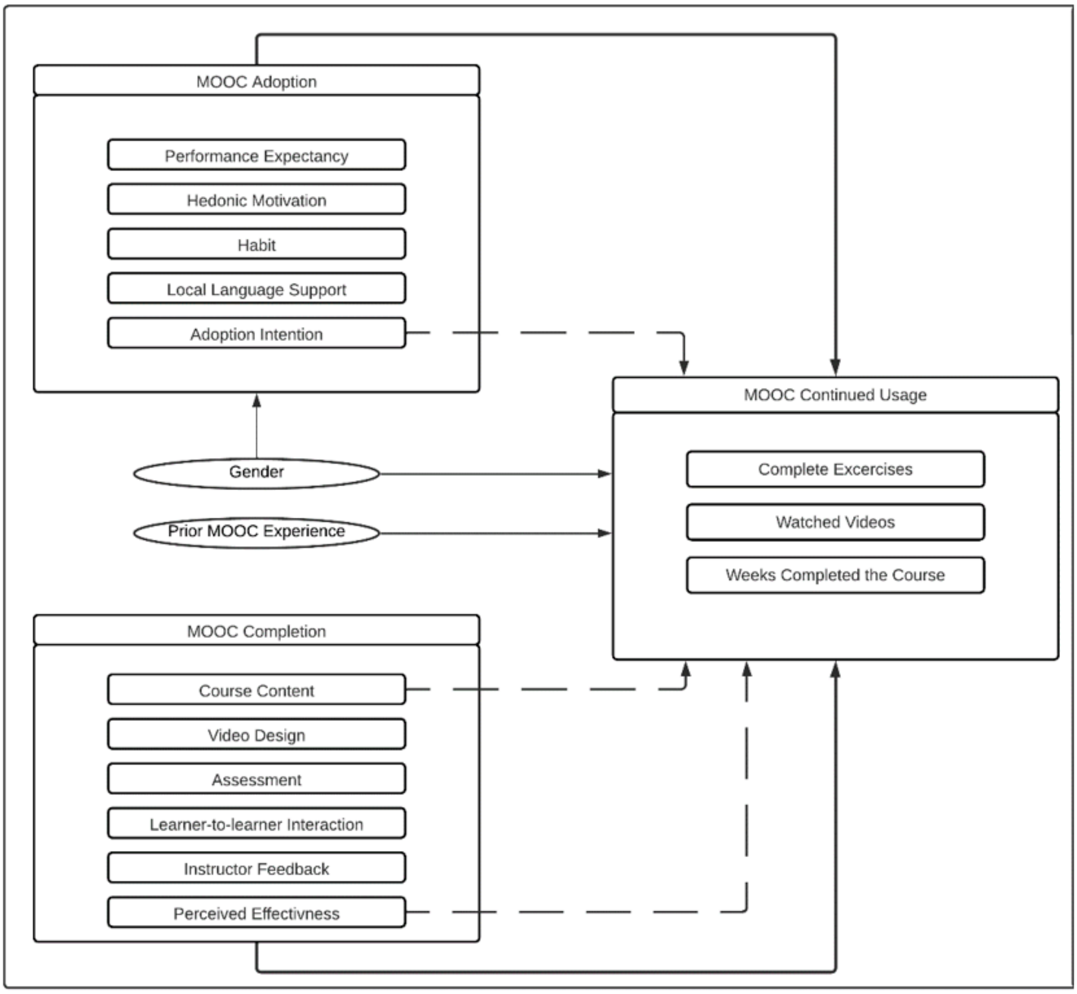

Figure 3. Effective MOOC Framework for Adoption, Completion, and Continued Usage of the Learner in the Context of Thailand.

As illustrated in Figure 3, adoption intention (AI) emerged as the most significant predictor of Actual Continued Usage (ACU), underscoring its pivotal role in shaping sustained learner engagement in ThaiMOOC. While previous studies have established AI as a strong determinant of MOOC adoption [39], our findings extend this relationship by demonstrating that AI significantly influences continued participation in MOOCs over time [106]. This distinction suggests that strategic interventions to enhance AI should not be limited to onboarding efforts but should also incorporate mechanisms to sustain engagement beyond the first MOOC experience.

Surprisingly, several commonly assumed predictors—such as performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FCs), hedonic motivation (HM), habit (HA), and local language support (LLS)—did not exhibit significant effects on ACU.

This finding challenges prior assumptions that these factors universally drive sustained engagement in online learning [107]. However, our results align with recent research indicating that MOOC persistence is more strongly associated with learners' intrinsic motivation and goal-directed behavior, rather than external enablers [106,108]. This suggests that future MOOC interventions should prioritize strengthening AI through structured engagement pathways, personalized learning incentives, and content relevance strategies rather than solely enhancing usability or accessibility.

A noteworthy qualitative insight further reinforces the importance of AI in learner retention. Open-text responses revealed that students who demonstrated higher AI levels frequently emphasized the role of local language support in facilitating engagement and comprehension. This aligns with studies indicating that localized instructional content enhances cognitive processing and self-efficacy, thereby strengthening students' commitment to continued learning [109]. The presence of such qualitative reinforcement provides a nuanced perspective, highlighting how language accessibility acts as a facilitator rather than a primary driver of sustained MOOC participation.

Likewise, the theme of 'Stay safe from COVID-19' demonstrated a contextual dimension that intersected with both adoption intention and open-text responses. We found that safety concerns necessitated the pandemic-induced adaptation towards remote learning. Many students' recognition of ThaiMOOC as a secure platform during the pandemic led to the resonance between adoption intention and an adaptive response to external circumstances. A study conducted in India also supports using MOOCs as a solution during the COVID-19 pandemic [110]. Based on our finding, it emphasizes the importance of online learning in providing education during these challenging times.

In terms of MOOC completion predictors, we found vital determinants that significantly influence students' ACU of ThaiMOOC. Course content (CC) and perceived effectiveness (PEF) were found to be significant predictors in promoting students' ACU. Those students who find themselves drawn to content that is not only informative but also engaging are inherently more likely to continue using ThaiMOOC. This finding aligns with Ucha's [111] study. The research found that students tend to find MOOCs easier to use when the CC is high quality, consequences the quality of CC is an essential factor in the continued usage of MOOCs. Likewise, PEF demonstrated a strong significant influence on ACU. The findings align consistently with prior research. Lee et al. [112] revealed the important role of perceived effectiveness in enhancing MOOC continued usage. When learners perceive MOOCs as effective, they demonstrate a higher likelihood of continued engagement. Conversely, the continued usage of MOOCs might confront obstacles, including the potential inefficacy of specific learning components and a decline in efficiency as students progress through the curriculum. These challenges can influence learners' perceptions of effectiveness, potentially impacting their continuous MOOC usage [113].

As illustrated in Figure 3, while video design (VD) emerged as a dominant theme in qualitative responses, our statistical analysis did not identify it as a significant predictor of ACU. This discrepancy suggests that although learners highly value well-crafted video content, other factors may exert a stronger influence on continued MOOC engagement. Nonetheless, open-ended responses emphasized the importance of video design (VD), course content (CC), assessment, and learner-to-learner interaction (LLI) in shaping the MOOC experience.

VD was the most frequently mentioned factor, with learners highlighting its role in enhancing comprehension, engagement, and overall course completion. Prior research supports these perceptions; Zhu et al. [114] found that short, well-structured videos improve student engagement in remote learning environments, leading to increased interaction time. Similarly, Guo et al. [85] suggest that MOOC video content is most effective when segmented into concise lessons of less than six minutes. These findings underscore the need for further exploration of how video format and presentation influence long-term learner retention in MOOCs.

Although video design (VD) was highly valued, our quantitative analysis did not identify VD as a statistically significant predictor of Actual Continued Usage (ACU). This discrepancy suggests that although learners appreciate well-designed videos, other factors may have a more substantial influence on their decision to continue engaging with MOOCs. Several explanations are possible. First, while learners may appreciate well-designed videos, this appreciation may not directly translate into a higher likelihood of continuing with future MOOCs. Other factors, such as course content relevance or perceived career benefits, could be more influential in that decision [115]. Second, the impact of VD might be more salient in the initial stages of MOOC engagement, aiding comprehension and motivation to complete the course, but its influence may diminish over time [116]. Third, our quantitative measure of VD may not have fully captured specific elements valued by learners, such as conciseness, clarity, and visual appeal, as highlighted in qualitative feedback [117]. Future research should explore this relationship further, employing more fine-grained VD metrics and examining potential moderating factors, such as learner preferences and prior online learning experience [118].

Additionally, our analysis indicates that MOOC video design—including production decisions, video length, graphics, and mobile compatibility—is closely associated with course content. This factor was the second most frequently mentioned in participant responses and has a significant influence on student engagement and the overall effectiveness of the MOOC learning experience. This finding is supported by a study by Deng and Gao [118], which suggests that effective MOOC video design involves creating accessible, easy-to-understand content with clear explanations, high-quality audio, and engaging visuals. Additionally, our qualitative analysis revealed that assessment plays a crucial role in influencing continued MOOC usage. The results demonstrated that students who completed assessments viewed them as valuable tutorials for their final exam. Consistent with the findings of Alexandron et al. [119], our study also indicates that unmarked assessments did not diminish the motivation of learners who completed the course. Remarkably, students perceive the value of unmarked assessments to prepare for the formal exam. Consistency between our results and prior studies [120–122] demonstrates the crucial role of assessment as a key factor in increasing completion and continued usage of ThaiMOOC. While our logistic regression analysis did not identify learner-to-learner interaction (LLI) as a statistically significant predictor of Actual Continued Usage (ACU), qualitative data from open-ended responses presents a more nuanced picture. A notable proportion of learners highlighted the value of LLI, particularly the online forum, as a safe space for asking questions, sharing solutions, and gaining diverse perspectives. Several students specifically noted that they preferred online interactions due to feeling less intimidated than in face-to-face settings. This suggests that LLI may play a more complex role in the MOOC experience than captured by our quantitative model. The lack of significance in the logistic regression could be due to several factors. First, LLI might be indirectly influencing ACU through other variables not included in the model, such as motivation or sense of community. Second, the effect of LLI might be heterogeneous, benefiting certain learners more than others depending on their individual preferences and learning styles. Third, the self-report nature of the open-ended responses might capture a different dimension of LLI than the behavioral data used in the quantitative analysis. Further research is needed to explore these potential explanations and fully understand the multifaceted role of LLI in continued MOOC engagement.

Regarding demographic predictors, our analysis reveals a significant gender effect on Actual Continued Usage (ACU): male participants exhibited lower levels of continued engagement than their female counterparts. This aligns with Healy [123], who found that gender plays a critical role in MOOC persistence and completion. Additionally, prior MOOC experience emerged as a strong predictor of ACU, suggesting that familiarity with the platform positively influences sustained engagement [124]. Our findings corroborate previous research in Estonia [125], where learners with prior MOOC exposure demonstrated significantly higher levels of continued participation. However, in contrast to earlier studies, we did not observe a significant effect of faculty affiliation on continued usage, indicating that other factors may play a more prominent role in influencing long-term engagement.

Our analysis of usage log file predictors further reinforces the importance of active participation in sustaining MOOC engagement. Specifically, completing exercises was a strong determinant of ACU, emphasizing the value of hands-on engagement. Similarly, watching more video content on ThaiMOOC correlated positively with increased engagement, suggesting that multimedia learning plays a crucial role in learner retention [14]. Progressing through the course curriculum also significantly influenced ACU, highlighting the importance of structured course design in fostering long-term participation. Notably, all students who did not complete their MOOC course opted not to enroll in any subsequent ThaiMOOC courses, suggesting that disengagement may stem from deeper underlying factors that require further investigation.

The findings of this study illustrate the multifaceted nature of MOOC engagement, emphasizing the interplay between adoption, completion, and continued usage. At the adoption stage, learners' initial decisions to enroll are driven by factors such as performance expectancy, effort expectancy, and social influence. A key finding is that adoption intention serves as a pivotal determinant of sustained MOOC usage, reinforcing the importance of fostering positive attitudes towards online learning. The completion stage is shaped by factors such as course content quality, perceived effectiveness, video design, assessment methods, and peer interaction, all of which act as enablers of continued engagement. Completion itself functions as a critical bridge between adoption and continued usage, with successful course completion leading to a greater likelihood of long-term participation.

In the continued usage stage, engagement is influenced by prior MOOC experience, active participation, gender, multimedia consumption, and structured progression through the course. The statistically significant association between initial adoption/completion and continued usage further supports the argument that early positive experiences play a vital role in sustaining long-term engagement. Our results show that approximately 81% of learners (n = 679) who successfully completed their initial courses exhibited a higher likelihood of maintaining MOOC participation, reinforcing the importance of designing learning environments that facilitate positive initial experiences.

By mapping out the key engagement drivers across these three stages, our study provides new insights into the cyclical relationship between adoption, completion, and continued usage in MOOCs. These findings offer practical implications for MOOC designers, educational institutions, and policy makers to develop strategies that enhance learner retention, improve course design, and foster long-term engagement. Future research should explore underlying factors influencing disengagement and investigate targeted interventions to promote sustained participation in online learning.

7. Practical Implications

The findings of this study present essential implications for educational institutions, MOOC providers, and policy makers aiming to improve learner retention and sustained engagement in online learning environments. By analyzing the interconnected stages of MOOC adoption, completion, and Actual Continued Usage (ACU), this research contributes to existing literature by illustrating the cyclical nature of engagement in MOOCs [126]. This cyclical approach emphasizes that understanding the factors influencing engagement at various stages can aid in developing effective evidence-based strategies to combat high dropout rates in MOOCs [127].

Demographic findings indicate a significant gender effect on continued engagement, suggesting that male participants tend to show lower levels of sustained engagement compared to their female counterparts [128]. This aligns with previous studies that highlight gender-based differences in online learning persistence [129]. To mitigate this disparity, institutions should focus on tailoring engagement strategies, such as integrating gamification, collaborative learning opportunities, and adaptive learning pathways that align with diverse motivational drivers [130]. Moreover, the role of prior MOOC experience is highlighted as a predictor of ACU, confirming that learners' familiarity with MOOC platforms significantly enhances continued engagement. This suggests an urgent need for structured onboarding programs to facilitate the adjustment for first-time users through orientation modules, introductory tutorials, and guided study plans [131].

Beyond demographic influences, this study identifies learner behavioral patterns as strong predictors of ACU. Active participation, including completing exercises and consuming video content, is crucial for maintaining learner engagement [132]. These findings underline the necessity for MOOC design to prioritize interactive and engaging learning components, such as structured assessments and progress-tracking features to foster sustained motivation [133]. While qualitative analyses suggest that video design plays a role in learner satisfaction, its direct impact on long-term engagement seems to be complicated by other factors, emphasizing the need for continuous investments in high-quality audiovisual content that effectively supports the learning process [134].

Furthermore, this study explores how course design and perceived effectiveness critically influence continued MOOC usage. The findings indicate that adoption intention and course content quality are key determinants of ACU. This underlines the need for MOOC designers to align their offerings with learner expectations and industry demands [127]. Integrating real-world case studies, industry-relevant skills, and personalized feedback mechanisms can significantly improve the perceived effectiveness of course offerings, enhancing knowledge retention and applicability [122]. The emphasis on learner-to-learner interactions, such as peer discussion forums and collaborative projects, further supports sustained commitment and persistence among learners in online education [135].

In conclusion, this research affirms actionable recommendations for enhancing learner retention in online education by highlighting the importance of targeted demographic strategies, learner behavioral engagement, and effective course design. By implementing these evidence-based approaches, educational institutions and MOOC providers can bolster student retention rates, enhance learning outcomes, and improve platform effectiveness, ultimately maximizing the impact of MOOCs on higher education and lifelong learning initiatives [131].

8. Limitations and Future Research

Despite the comprehensive nature of this study, several limitations should be acknowledged. First, this study was conducted within a single university context, which may limit the generalizability of the findings to broader educational settings. Future research should expand the scope by incorporating data from multiple institutions and diverse academic disciplines to validate the robustness of the results across different educational environments.

Second, the sample exhibited a significant gender imbalance, with female participants comprising the majority. This may have influenced findings related to continued MOOC engagement, as prior research suggests that gender differences affect online learning behaviors. To mitigate this limitation, future research should adopt quota sampling techniques or apply weighted statistical adjustments to ensure a more balanced representation of genders. Additionally, targeted recruitment strategies—such as stratified sampling—could help diversify participant demographics and enhance the generalizability of findings.

Third, while this study employed a longitudinal design to capture learner behavior over time, self-selection bias remains a concern. Since participation was voluntary, highly motivated learners may have been overrepresented, potentially skewing the predictive power of certain engagement factors. Future studies should consider stratified random sampling to ensure a more representative sample of MOOC participants, including those with varying levels of prior online learning experience.

Fourth, the logistic regression model used to predict continued MOOC engagement showed class imbalance, with higher accuracy in predicting students who continued enrolling (97%) compared to those who discontinued (68%). This suggests that alternative machine learning approaches, such as ensemble methods or deep learning models, could improve the predictive accuracy for non-continuing learners. Additionally, integrating latent variable modeling techniques, such as structural equation modeling (SEM), may provide deeper insights into the mediating relationships among key engagement predictors.

Fifth, this study was conducted during the COVID-19 pandemic, a period marked by unique learning conditions and widespread reliance on online education. The factors influencing MOOC engagement during this time may differ in a post-pandemic educational landscape, where blended learning models and in-person instruction are increasingly reintegrated. Future research should examine whether the predictors of Actual Continued Usage (ACU) identified in this study remain stable as higher education institutions transition to post-pandemic learning environments.

Lastly, while this study employed a mixed-methods approach, the qualitative analysis primarily relied on open-ended survey responses. Future research could employ in-depth interviews or focus groups to provide richer insights into learner motivations and barriers to sustained MOOC engagement. Longitudinal qualitative studies could further explore how learners' attitudes and perceptions evolve over multiple MOOC experiences, offering a more nuanced understanding of the factors driving continued participation.

By addressing these limitations, future research can refine and expand upon the findings of this study, contributing to the ongoing development of effective MOOC engagement strategies tailored to diverse learner needs.

9. Conclusions

This study presents a longitudinal examination of the factors influencing MOOC engagement, focusing on adoption, completion, and Actual Continued Usage (ACU) within the context of ThaiMOOC. By integrating survey data, usage log analysis, and open-ended responses, this research provides a comprehensive understanding of learner behavior in online education.

The findings highlight adoption intention (AI) as the most significant predictor of continued MOOC engagement, reinforcing the importance of fostering positive learner attitudes from the initial stages of enrollment. Course content (CC) and perceived effectiveness (PEF) also emerged as critical factors influencing sustained participation, underscoring the necessity of high-quality, engaging instructional materials that align with learner expectations and professional aspirations.

Surprisingly, several commonly assumed predictors—including performance expectancy, effort expectancy, and social influence—did not exhibit a statistically significant impact on ACU. This suggests that intrinsic motivation and content relevance may play a more dominant role than external factors in shaping long-term MOOC engagement. Furthermore, gender differences were observed, with female learners demonstrating higher continued MOOC usage rates than their male counterparts, aligning with prior research on persistence in online education. Prior MOOC experience also significantly influenced ACU, indicating that learners with previous exposure to MOOCs are more likely to sustain engagement in subsequent courses.

Although video design (VD) was highly valued in qualitative responses, it did not appear as a statistically significant predictor of ACU. This finding suggests that while high-quality videos enhance learner satisfaction, they may not be the primary driver of continued MOOC engagement. Similarly, while learners acknowledged the importance of peer interaction and assessment, these factors did not exhibit strong predictive power for sustained participation, indicating that future research should explore their potential indirect effects on engagement outcomes.

From a methodological standpoint, this study demonstrates the effectiveness of mixed-methods research in MOOC engagement analysis, bridging the gap between quantitative behavioral data and qualitative learner experiences. The integration of logistic regression with open-text content analysis provided a richer, more contextualized understanding of MOOC engagement dynamics.

The implications of these findings extend beyond ThaiMOOC, offering valuable insights for MOOC designers, educators, and policy makers seeking to enhance online learning experiences. To improve long-term learner retention, MOOC platforms should prioritize strategies that strengthen adoption intention, optimize course content quality, and ensure perceived effectiveness. Additionally, designing onboarding programs that support first-time MOOC users and incorporating adaptive learning features could further enhance engagement and knowledge retention.

As online education continues to evolve, this study contributes to the growing body of literature on MOOC engagement and learner retention strategies. By addressing the identified limitations and expanding research across diverse learning contexts, future studies can refine these findings and further optimize the design of MOOCs to support lifelong learning and professional development.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee of Brunel University London via the Brunel Research Ethics Online (BREO) system (Approval Code: 22294-LR-Feb/2021-31300-1, Approval Date: 16 February 2021 for Phase 1; Approval Code: 31169-LR-Jul/2021-33616-1, Approval Date: 4 August 2021 for Phases 2 and 3).

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The data supporting this study are available upon reasonable request from the corresponding author. Restrictions apply due to a confidentiality agreement established during the ethical approval process at Brunel University London and the conditions set by the gatekeeper who granted permission for data collection. These restrictions specify that the collected data should only be accessed by the researchers involved in this study.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Survey Items of Phase 1 MOOC Adoption.

Factor		Questions	Citation
Performance Expectancy	PE1	I find ThaiMOOC useful for my learning	[35]
	PE2	Using ThaiMOOC helps me complete learning activities more quickly	
	PE3	Using ThaiMOOC increases my productivity	
	PE4	Using ThaiMOOC improves my chances of achieving a better grade	
Effort Expectancy	EE1	Learning how to use ThaiMOOC is easy for me	
	EE2	My interactions with ThaiMOOC are clear and understandable	
	EE3	I find ThaiMOOC easy to use	
	EE4	It is easy for me to become skilled at using ThaiMOOC	
Social Influence	SI1	People who are important to me, such as my family, believe that I should use ThaiMOOC	
	SI2	People who influence my behavior, such as my friends, think that I should use ThaiMOOC	
	SI3	People whose opinions I value, such as my teachers, prefer that I use ThaiMOOC	
	SI4	In general, my university supports the use of ThaiMOOC	
Facilitating Conditions	FC1	I have the necessary resources to use ThaiMOOC	
	FC2	I have the necessary knowledge to use ThaiMOOC	
	FC3	ThaiMOOC is compatible with other technologies I use	
	FC4	I can get help from others when I face difficulties using ThaiMOOC	
Hedonistic Motivation	HM1	Using ThaiMOOC is fun.	
	HM2	Using ThaiMOOC is enjoyable.	
	HM3	Using ThaiMOOC is entertaining.	
Habit	HA1	Using ThaiMOOC has become a habit for me	
	HA2	I am in favor of using ThaiMOOC	
	HA3	I feel the need to use ThaiMOOC	
	HA4	Using ThaiMOOC feels natural to me	
Local Language Support	LL1	MOOC courses provided in the Thai language are easier to understand and learn	[76]
	LL2	MOOC courses offered in Thai enhance my understanding of the course content	
	LL3	Communicating with instructors and learners in ThaiMOOC using the Thai language is more convenient for me	
	LL4	I will face language difficulties when using an educational platform that does not support the Thai language	
	LL5	Thai-language MOOC platforms benefit Thai students who are interested in learning	
Adopting Intention	AI1	I intend to continue using ThaiMOOC in the future	[35]
	AI2	I will make an effort to use ThaiMOOC in my daily life	
	AI3	I plan to continue using ThaiMOOC frequently	

1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly agree.

Table A2. Survey Items of Phase 2 MOOC Completion.

Factors		Questions	Citation
Instructor-to-Learner Interaction	ILI1	I felt comfortable asking questions throughout this course	[94]
	ILI2	The instructor responded to my questions in a timely manner	
	ILI3	The instructor was easily accessible	
	ILI4	I felt free to express and explain my own views throughout this course	
Instructor Support	IS1	The instructor played an important role in facilitating learning	
	IS2	The instructor actively contributed to discussions in this course	
	IS3	The instructor was helpful when students encountered problems	
	IS4	I interacted with the instructor in this course	
	IS5	The instructor emphasized the relationships between topics	
Instructor Feedback	IF1	The instructor was responsive to student concerns	[136]
	IF2	The instructor provided timely feedback on assignments, exams, or projects	
	IF3	The instructor provided helpful and timely feedback on assignments, exams, or projects	
	IF4	I felt that the instructor cared about my individual learning experience in this course	
Learner-to-Learner Interaction	LLI1	Group work contributed significantly to my learning experience	[94]
	LLI2	The group size was appropriate for the course objectives	
	LLI3	Student interaction was an important part of the learning process in this course	
	LLI4	This course provided opportunities to learn from other students	
	LLI5	I had sufficient opportunities to interact with other students in this course	
Course Content	CC1	This course effectively challenged me to think critically	
	CC2	Course assignments were interesting and engaging	
	CC3	This course was up-to-date with developments in the field	
	CC4	Student evaluation methods, such as projects, assignments, and exams, aligned with the learning objectives	
	CC5	This course included applied learning and problem-solving activities	
Course Structure	CS1	The structure of the course modules was well-prepared and organized	
	CS2	Projects and assignments were clearly explained	
	CS3	I understood what was expected of me in this course	
Assessment	AS1	I could see how the assessable work aligned with the learning objectives	[95]
	AS2	The feedback on my assessable work helped me improve my learning and study strategies	
	AS3	The feedback on my assessable work helped clarify concepts I had not fully understood	
Video Design	VD1	I found that shorter videos (less than 10 min) increased my engagement.	[85]
	VD2	I found videos that interspersed an instructor's talking with slides more engaging than slides alone	
	VD3	I found that videos produced in a more informal setting were more engaging than those in a formal setting	
	VD4	I found that videos where instructors spoke at a slightly faster pace increased my engagement	
	VD5	I found that videos where instructors spoke with high enthusiasm increased my engagement	
Perceived Effectiveness	PER1	I would recommend this course to my friends or colleagues	[94]
	PER2	I have learned a lot in this course	
	PER3	I have enjoyed taking this course	

1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly agree.

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