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Gamification and MOOC persistence: an integrated UTAUT2–SDT–engagement model

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ABSTRACT

Massive open online courses (MOOC) completion rates remain low despite the continued growth of online learning platforms. This study examined the factors influencing learning persistence (PERS) in gamified MOOCs using an integrated unified theory of acceptance and use of technology 2-self-determination theory (UTAUT2–SDT)–engagement (ENG) model. A cross-sectional survey was conducted with 200 MOOC learners in Thailand, and the data were analyzed using partial least squares structural equation modeling (PLS-SEM). The results showed that student ENG significantly predicted behavioral intention (BI) ($\beta = 0.352, p < 0.001$) and PERS ($\beta = 0.278, p < 0.001$), whereas BI did not significantly predict PERS ($\beta = 0.143, p = 0.063$). Need satisfaction (NS) also had significant positive effects on ENG ($\beta = 0.322, p < 0.001$) and hedonic motivation (HM) ($\beta = 0.305, p < 0.001$). These findings indicate an intention–behaviour gap in MOOCs and suggest that sustained ENG is more important than initial intention for explaining PERS. The study highlights the importance of designing gamified MOOCs that support learners' autonomy, competence, and relatedness to strengthen long-term participation.

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1. INTRODUCTION

Persistently low completion rates of 12–13% in massive open online courses (MOOCs) represent a major challenge for educational institutions and learners worldwide [1]. Despite the transformative potential of MOOCs to democratize access to quality education, the majority of enrolled learners fail to complete their courses, resulting in lost opportunities for skill development and career advancement. Addressing this persistence (PERS) challenge requires a theoretical framework that moves beyond simple technology acceptance to account for the motivational and engagement (ENG)-related mechanisms that sustain learning behavior over time.

The unified theory of acceptance and use of technology 2 (UTAUT2) model [2], [3] has proven effective in predicting technology adoption through key constructs such as performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), and habit [2], [3]. Nevertheless, UTAUT2 by itself cannot fully account for the transition from adoption intention to sustained learning PERS, as this transition necessitates an understanding of motivational quality beyond the mere magnitude of intention. Self-determination theory (SDT) [4] argues that sustained PERS over time is contingent upon the fulfillment of three core psychological needs: autonomy, competence, and relatedness. Combining SDT with UTAUT2 provides the motivational quality dimension absent from UTAUT2 constructs, explaining how intrinsic need satisfaction (NS) fosters high-quality engagement and sustained persistence.

Gamification—defined as the deliberate incorporation of game-design mechanics into non-game environments—has demonstrated considerable promise for elevating learner engagement in educational contexts [1]. Though effects are context-dependent [5], some elements merely boost superficial activities without fostering deeper intrinsic motivation [6]. Despite growing literature on MOOC adoption and motivation, few studies have integrated UTAUT2, SDT, and multidimensional student ENG to explain PERS in gamified MOOC contexts. Specifically, the intention–behavior gap—the disconnect between stated intention and actual PERS—remains theoretically underexplained, and multidimensional ENG has not been positioned as the key mediating mechanism bridging motivational antecedents and PERS outcomes.

To address these gaps, this study develops and empirically validates an integrated UTAUT2–SDT–ENG model with gamification components. This model is designed to explain both behavioral intention (BI) and learning PERS within the context of gamified MOOCs. Specifically, the study will: i) identify the structural role of specific gamification elements in fostering the psychological needs of autonomy, competence, and relatedness; ii) investigate the causal pathway from UTAUT2 predictors through NS and ENG to PERS; and iii) the mediating role of ENG in bridging motivational antecedents and PERS outcomes.

This study makes three contributions: i) validating the first integrated UTAUT2–SDT–ENG model for gamified MOOCs; ii) empirically demonstrating the intention–behavior gap, showing that engagement quality is more predictive of persistence than BI; and iii) repositioning student engagement as the primary driver of persistence. Practically, the findings provide design guidelines for MOOC developers to employ mechanism-driven gamification supporting psychological needs (autonomy, competence, and relatedness) and fostering sustained engagement.

2. PROPOSED MODEL

2.1. References model

Sustaining learner participation in MOOCs remains a formidable challenge that demands a thorough theoretical account. Conventional technology acceptance frameworks fail to capture the full complexity of the processes underlying learning PERS. An integrated model is therefore needed—one that bridges technology acceptance factors, psychological need fulfillment, and ENG [7], [8].

Within this model, the UTAUT2 constructs of PE and EE are hypothesized to directly influence BI (H1 and H2). PE refers to the learner's belief that utilizing the MOOC will enhance their learning performance and academic outcomes. EE, in turn, pertains to the perceived ease of use of the system and the degree of effort required to operate it. Together, these two predictors establish the foundational intention for continued use of the MOOC system [2], [3], [9].

SDT provides a framework for distinguishing the quality of motivation based on the fulfillment of three basic psychological needs: autonomy, competence, and relatedness. The satisfaction of these needs is causally associated with higher-quality motivational states, such as intrinsic and identified regulation, which in turn promote behavioral PERS. Gamification is conceptualized as a set of 'design affordances' (e.g., adaptive feedback, mastery badges, branching quests, social cooperation) that must be deliberately mapped to support these psychological needs. This mapping follows a specific causal logic (mechanic→need→motivational quality) aimed at mitigating outcome variability and avoiding the pitfall of superficial ENG [4], [10].

NS encompasses three psychological dimensions: autonomy (volitional control over learning), competence (feeling capable and effective), and relatedness (sense of connection with others). This construct has two roles in the proposed model: it directly influences ENG (H3) and enhances HM (H4), defined as motivation derived from the pleasure and enjoyment of learning [11]. HM mediates between NS and ENG. When psychological needs are met, learners experience pleasure and enjoyment, which in turn enhances ENG (H5). A MOOC design engineered to support these psychological needs is expected to amplify both the learner's HM and, consequently, their overall ENG [12].

Student engagement is conceptualized as a multidimensional construct comprising three dimensions: behavioral ENG (active participation), emotional ENG (positive affective responses), and cognitive ENG (strategic effort and deep learning strategies). This construct mediates between motivational antecedents and outcomes, influencing both BI (H6) and PERS (H8) [13]. High-quality ENG thus reinforces both the learner's intention to continue and serves as a direct driver of PERS.

Persistence, which encompasses both course completion and continued use, is positioned as the terminal outcome in the proposed model. Two principal pathways are hypothesized to converge on this outcome. The first is the conventional path mediated by BI (H7), a route well-established in traditional technology acceptance theories. The second pathway posits a direct influence from ENG on PERS (H8). This latter connection suggests that robust ENG can drive PERS directly, potentially bypassing the prerequisite of forming an explicit BI [14].

This integrated model bridges technology acceptance, motivation, and ENG theories, delineating two pathways to PERS: one mediated by intention and another driven directly by ENG. Empirical validation of this model is expected to inform effective gamification design strategies for reducing MOOC dropout rates [15]. In particular, the application of gamification elements designed to support the needs for autonomy, competence, and relatedness is highlighted as a promising strategy to bolster both HM and the multifaceted dimensions of ENG [11].

2.2. Hypotheses

A systematic literature review by Yuliani *et al*. [16] spanning 2012–2024 confirmed that PE is a primary predictor of BI in digital technology adoption contexts, directly supporting H1. The first hypothesis was formulated as H1: PE→BI. Moreover, Permatasari *et al.* [17] demonstrated using partial least squares structural equation modeling (PLS-SEM) with 400 Generation Z users, that EE substantially shapes BI and actual use behavior, with BI serving as a pivotal mediator, supporting H2. The second hypothesis was formulated as H2: EE→BI.

Nguyen-Viet and Nguyen-Viet [18] found that satisfying basic psychological needs through gamified learning activities was significantly and positively associated with higher levels of ENG in Vietnamese educational contexts, supporting H3. The third hypothesis was formulated as H3 : NS→ENG. Furthermore, Huang *et al.* [19] demonstrated that concurrent satisfaction of psychological needs and positive hedonic experiences is a central determinant of user interaction in immersive virtual environments, confirming that NS amplifies HM (H4). The fourth hypothesis was formulated as H4: NS→HM.

Qu and Wu [20] established a positive association between HM and learner ENG in English language learning using ChatGPT, with joy, focused immersion, and perceived control as significant moderators, providing empirical support for H5. The fifth hypothesis was formulated as H5 : HM→ENG. In addition, Zhou *et al.* [21] found significant positive associations among ENG (behavioral, emotional, and cognitive dimensions) and teachers' BI in continuous TPACK development, directly corroborating H6. The sixth hypothesis was formulated as H6: ENG→BI.

Chiu [22] established that BI functions as a significant predictor of PERS in online learning environments, confirming a positive relationship between intention and continued learning behavior (H7). Thus, the seventh hypothesis was formulated as H7: BI→PERS. In addition, Jerez [23] confirmed that ENG is a meaningful driver of PERS among mature-aged university learners, providing empirical validation for H8 across a population that regularly faces unique barriers to continuing education. The eighth hypothesis was formulated as H8: ENG→PERS.

2.3. Proposed model

This research proposes an integrated model synthesizing UTAUT2, SDT, and the student engagement framework to elucidate BI and learning persistence in gamified MOOCs. The model comprises eight hypotheses (H1–H8): PE and EE (UTAUT2) predict BI (H1, H2); NS directly influences ENG (H3) and HM (H4); HM enhances ENG (H5); ENG predicts BI (H6) and PERS (H8); and BI predicts PERS (H7). This interdisciplinary framework positions student engagement as the key mediator bridging motivational antecedents and persistence outcomes, as depicted in Figure 1.

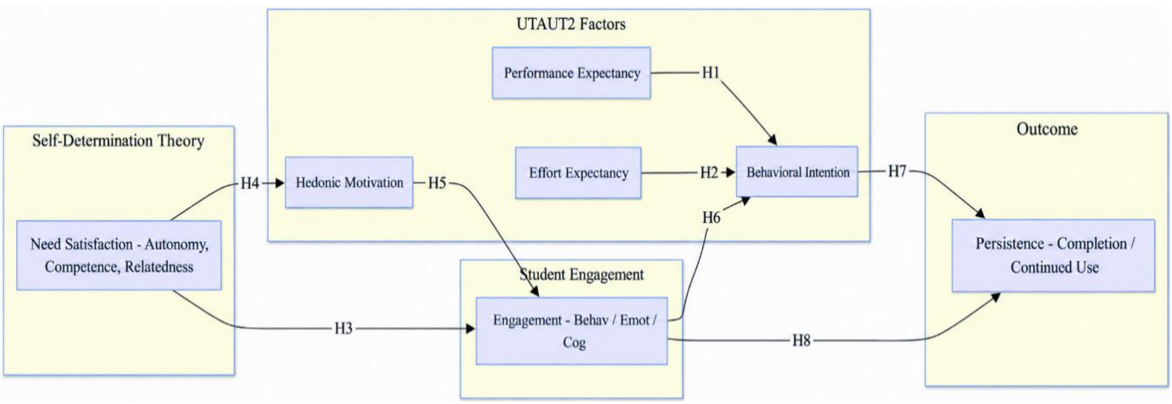

Figure 1. Proposed UTAUT2–SDT–ENG model showing hypothesized relationships among gamification, psychological needs, ENG, and PERS in MOOCs

3. METHOD

3.1. Determining the subject and sample size

The target population comprised active MOOC learners enrolled in gamified courses on major platforms (e.g., Coursera, edX, and FutureLearn) in Thailand. The sampling frame consisted of learners accessible through online MOOC communities and university digital learning centers. Purposive sampling was employed as the primary sampling strategy, which is appropriate for this study for three reasons. First, the research questions require participants with direct experience of gamified MOOC features; random sampling would likely yield a high proportion of ineligible respondents with insufficient exposure. Second, purposive sampling allows precise control over inclusion criteria, ensuring that all participants possessed the minimum level of platform experience necessary to meaningfully assess the model constructs. Third, this approach is consistent with prior MOOC research employing similar criterion-based sampling strategies. Participants were recruited based on two inclusion criteria: i) a minimum of four weeks of active experience on a gamified MOOC platform and ii) completion of at least 25% of course content, ensuring sufficient ENG to evaluate gamification elements. A total of 200 usable responses were obtained from 250 distributed surveys, yielding a response rate of approximately 80%.

To address the limitations of the sample size, several methodological modifications are proposed to uphold the analytical rigor and validity of the findings. Firstly, the adoption of PLS-SEM, facilitated by SmartPLS software, is favored over the covariance-based structural equation modeling (CB-SEM) approach. This preference is grounded in PLS-SEM's established robustness with smaller sample sizes and non-normally distributed data [24]. Secondly, implementing a bias-corrected and accelerated (BCa) bootstrapping procedure with 5,000 resamples will yield robust estimates for standard errors and confidence intervals, thereby mitigating potential sampling variability [25]. Thirdly, prioritizing model parsimony is crucial. This can be achieved either through the parceling of highly correlated constructs or by sequentially testing sub-models in place of the fully integrated framework. Such a strategy serves to decrease the parameter-to-observation ratio, which in turn enhances overall model stability.

3.2. Instrument development and data collection

The research instrument was constructed by adapting and integrating items from well-established theoretical frameworks, namely the UTAUT2 [3], SDT [19], and the literature on student engagement [26]. These items were specifically tailored to the context of learning within gamified MOOCs. The questionnaire was designed to measure several key constructs. From the UTAUT2 framework, it included PE and EE. Drawing from SDT, the instrument assesses Basic Psychological Need Satisfaction, encompassing the fundamental needs for autonomy, competence, and relatedness. ENG was evaluated across its behavioral, emotional, and cognitive dimensions. Furthermore, the instrument incorporated HM. The designated outcome variables were BI and PERS in learning [27], [28]. All items were measured on a 5-point Likert scale.

Data were collected using a purposive sampling method. The inclusion criteria stipulated that participants must be learners in a MOOC with a minimum of four weeks of experience on a gamified platform and have completed at least 25% of the course content [29]. The data collection was administered via an online survey platform over an eight-week period. To uphold data integrity, several quality control measures were implemented. These included monitoring response completion times, embedding attention-check questions within the survey, and screening for duplicate submissions [30]. This rigorous approach was designed to ensure sufficient statistical power for testing the proposed model [31]. The instrument was validated through expert review (n=5) and pilot testing (n=30), yielding acceptable reliability (α>0.70) [32].

3.3. Data analysis

PLS-SEM was employed using SmartPLS 4.0. PLS-SEM is well-suited for exploratory research as it imposes no multivariate normality assumption and accommodates smaller sample sizes [30]. Analysis proceeded in two stages: measurement model assessment and structural model evaluation. The measurement model was evaluated for significant outer loadings (>0.7), convergent validity (Cronbach's α>0.7, Composite reliability (CR)>0.7, average variance extracted (AVE)>0.5), and discriminant validity (Fornell-Larcker criterion, HTMT<0.9) [29], [33]. The structural model was assessed using path coefficients (β>0.2), t-values (>1.96), p-values (<0.05), and R^2 (>0.1). Bootstrapping with 5,000 resamples was applied to test hypothesis significance [29], [32], [34]–[36]. To address common method bias (CMB), Harman's single-factor test was conducted. The first unrotated factor accounted for 28.4% of total variance, substantially below the 50% threshold [33], indicating that CMB does not pose a serious threat to the validity of conclusions.

4. RESULTS AND DISCUSSION
4.1. Participant demographics
The sample of 200 participants was gender-balanced (49% male, 51% female) and predominantly comprised young adults aged 18-35 years (81.5%), with most holding bachelor's degrees (56%) and 44% holding postgraduate qualifications. MOOC experience varied from 4-8 weeks (39%) to over 16 weeks (19%), with diverse course completion rates (25-50%: 47%; 51-75%: 33.5%; >75%: 19.5%), aligning with the study's focus on PERS in gamified learning environments.

4.2. Significant loading
The analysis of the outer loadings for the measurement model revealed that all indicators demonstrated acceptable values, ranging from 0.767 to 0.883. These values comfortably exceed the minimum recommended threshold of 0.70 for PLS-SEM research. Notably, the indicators with the highest loadings included NS1 (0.883 on NS), BI2 (0.882 on BI), PERS2 (0.856 on PERS), PE2 (0.851 on PE), and ENG2 (0.848 on ENG), indicating their superior ability to represent their respective latent variables. Conversely, while EE3 (0.767 on EE) and NS2 (0.778 on NS) registered the lowest loadings, they remained well within the acceptable range. The consistent and strong performance of all indicators across the latent variables (BI, EE, ENG, HM, NS, PE, and PERS) provides robust evidence for the convergent validity of the measurement model. This confirms that each indicator reliably measures its intended underlying construct, thereby establishing a solid foundation for the subsequent structural model analysis [37].

4.3. Convergent validity
The assessment of reliability and validity for the seven latent constructs indicated that the measurement model possesses acceptable quality overall. CR values for all constructs ranged from 0.827 to 0.879, comfortably exceeding the standard 0.70 threshold [38] and thus demonstrating strong internal consistency. Cronbach's alpha coefficients were observed in the range of 0.689 to 0.794. It is noted that only the EE construct (α=0.689) fell marginally below the conventional 0.70 benchmark. For convergent validity, the AVE for all constructs surpassed the minimum threshold of 0.50, with values between 0.614 and 0.708. This result signifies that each latent variable explains a majority of the variance in its associated indicators, outweighing the variance attributable to measurement error. A comparative analysis revealed that the BI construct exhibited the highest measurement quality across all indicators. Conversely, while the EE construct registered the lowest scores, its metrics remained within acceptable parameters [39]. Collectively, these findings affirm the suitability of the measurement model, establishing a robust foundation for the subsequent structural relationship analysis.

4.4. Discriminant validity
The evaluation of discriminant validity, conducted using the heterotrait-monotrait ratio (HTMT) criterion, confirmed the distinctiveness of the seven latent constructs. The analysis revealed that all HTMT values, which ranged from 0.292 to 0.590, fall well below both the stringent 0.85 threshold and the more lenient 0.90 benchmark [36]. This provides strong evidence that each construct is empirically distinct and measures a unique underlying concept. Specifically, the highest inter-construct correlation was observed between BI and ENG (HTMT=0.590), whereas the lowest was found between EE and PERS (HTMT=0.292). These results collectively affirm that the measurement model possesses sufficient discriminant validity [34]. This confirmation is critical, as it supports the use of these variables in the subsequent SEM. It ensures that each construct can be independently analyzed without significant concerns regarding measurement overlap or conceptual redundancy, thereby preventing potential multicollinearity issues [40].

4.5. Predictive relevance
An examination of the coefficient of determination (R^2) revealed varying levels of explanatory power across the endogenous constructs. The model demonstrated the highest predictive accuracy for the BI construct, with an R^2 value of 0.268 (adjusted R^2=0.253). This indicates that the exogenous variables collectively account for 26.8% of the variance in BI. Following this, the ENG construct exhibited an R^2 of 0.248 (adjusted R^2=0.241), signifying that the model explains 24.8% of the variance in user ENG. In contrast, the model showed more limited explanatory power for the HM and PERS constructs. The R^2 for HM was 0.093, while for PERS it was 0.134, corresponding to explanatory capacities of 9.3% and 13.4%, respectively. Notably, the minimal discrepancies between the R^2 and adjusted R^2 values for all constructs (0.015, 0.007, 0.005, and 0.005, respectively) suggest that the model is stable and not susceptible to overfitting. However, the relatively modest R^2 values for HM and PERS are indicative of the inherent complexity of human behavior. This outcome suggests the influence of other external factors not incorporated into the current model, a common characteristic in behavioral science research where phenomena are often subject to high variability and multifactorial influences.

4.6. Structural model results and hypotheses testing

ENG emerged as the strongest predictor of both BI and PERS. Specifically, ENG was the dominant driver of BI (β=0.352) and exerted a direct, significant effect on PERS (β=0.278). Notably, BI did not significantly predict PERS (β=0.143), revealing a clear intention–behavior gap in the MOOC context. Among the UTAUT2 predictors, PE was a significant predictor of BI (β=0.200), while EE was not significant (β=0.099), suggesting that learners prioritize learning value over ease of use. NS proved to be a key motivational driver, significantly influencing both ENG (β=0.322) and HM (β=0.305). However, the model's explanatory power for HM and PERS remained low (R^2(HM)=0.093; R^2(PERS)=0.134), while the R^2 values for ENG and BI were moderate (R^2(ENG)=0.248; R^2(BI)=0.268).

Our PLS-SEM analysis revealed two key drivers of BI among MOOC learners. First, we found that ENG strongly predicts intention to continue (β=0.352, t=5.600, p<0.001), suggesting that learners who actively participate and feel emotionally connected are more likely to plan for continued use. Second, PE also matters (β=0.200, t=2.918, p=0.004), indicating that perceived usefulness influences learners' commitment. Interestingly, ease of use (EE) showed no significant effect (β=0.099, t=1.391, p=0.164). This finding suggests that in gamified MOOCs, learners care more about value and ENG than convenience—perhaps because most participants are already comfortable with online platforms. The results support SDT's emphasis on psychological needs. When learners felt autonomous, competent, and connected (NS), they showed higher ENG (β=0.322, t=4.848, p<0.001) and experienced more enjoyment (HM: β=0.305, t=4.941, p<0.001). This enjoyment, in turn, further boosted their ENG (β=0.294, t=4.698, p<0.001). In practical terms, this creates a positive cycle: satisfying learners' basic needs makes learning more enjoyable, which then sustains their active participation. This finding highlights why gamification should focus on supporting autonomy, competence, and relatedness rather than just adding superficial game elements like points or badges.

Perhaps the most striking finding concerns what actually drives PERS. ENG directly predicted whether learners continued with the course (β=0.278, t=3.698, p<0.001), supporting H8. However, BI did not significantly predict PERS (β=0.143, t=1.861, p=0.063), leading us to reject H7. This reveals an important gap between what learners say they will do and what they actually do. Traditional technology acceptance models assume that if people intend to use a system, they will. Our findings challenge this assumption in the MOOC context. Simply wanting to complete a course is not enough—what matters more is whether learners stay actively engaged throughout. This suggests that MOOC designers should focus less on generating initial enthusiasm and more on creating conditions that sustain ongoing participation. The quality of the learning experience matters more than initial motivation. These results reshape our understanding of MOOC PERS. Rather than following the traditional path of motivation→intention→behavior, we found that ENG serves as the critical bridge. When gamified MOOCs satisfy learners' needs for autonomy, competence, and connection, they create engaging experiences that directly sustain participation—regardless of whether learners initially intended to complete the course. Practically speaking, this means that making a MOOC easier to use (EE) is less important than making it engaging and need-supportive. MOOC developers should prioritize design features that foster genuine ENG: meaningful choices (autonomy), appropriately challenging activities (competence), and opportunities for peer interaction (relatedness). These elements appear more crucial for retention than simply reducing friction or generating initial interest. Detailed results are presented in Table 1.

Table 1. Hypotheses testing result

Hypotheses	Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values (<0.05)	Findings
H1	PE->BI	0.2	0.203	0.069	2.918	0.004	Accepted
H2	EE->BI	0.099	0.107	0.071	1.391	0.164	Rejected
H3	NS->ENG	0.322	0.323	0.066	4.848	<0.001	Accepted
H4	NS->HM	0.305	0.311	0.062	4.941	<0.001	Accepted
H5	HM->ENG	0.294	0.297	0.063	4.698	<0.001	Accepted
H6	ENG->BI	0.352	0.35	0.063	5.6	<0.001	Accepted
H7	BI->PERS	0.143	0.145	0.077	1.861	0.063	Rejected
H8	ENG->PERS	0.278	0.282	0.075	3.698	<0.001	Accepted

4.7. Discussion

This study developed and empirically validated an integrated UTAUT2–SDT–ENG model, incorporating gamification elements, to explain the complex pathway from technology acceptance to learning PERS in gamified MOOCs. The findings address the identified research gaps and yield several key insights with implications for both theoretical advancement and practical application in online education. The discussion that follows interprets each key finding in relation to the existing literature, considers alternative explanations, and articulates the theoretical and practical contributions of the study.

A central and novel contribution of this research is the empirical identification of ENG as the primary mediator linking motivational antecedents (NS and HM) to behavioral outcomes (BI and PERS). ENG was the strongest predictor of BI (β=0.352, p<0.001) and exerted a direct, significant effect on PERS (β=0.278, p<0.001), demonstrating that ENG functions as both an outcome of motivational processes and a driver of PERS. This dual role of ENG—as both a mediator and a direct predictor—represents a key theoretical advancement over prior models that treat ENG as a peripheral or outcome variable. This finding aligns with the previous works [21], [23], which emphasizes the importance of multidimensional ENG in fostering sustainable learning outcomes.

The significant positive influence of NS on both ENG (β=0.322, p<0.001) and HM (β=0.305, p<0.001) confirms the central role of psychological need fulfillment in fostering intrinsic motivation. This finding aligns with SDT, as proposed by Deci and Ryan [4]. The theory posits that the fulfillment of needs for autonomy, competence, and relatedness forms the fundamental basis for intrinsic motivation and enduring pro-behavioral outcomes. The positive influence of HM on ENG (β=0.294, p<0.001) highlights the significance of pleasure and enjoyment within the learning process. This finding corroborates the work of Qu and Wu [20], whose study on ChatGPT adoption for English learning also identified a positive correlation between HM and learner ENG. This discovery holds an important implication for the design of gamified MOOCs, suggesting that creating an enjoyable and compelling learning experience is not merely a superficial addition. Rather, it functions as a key mechanism that bridges the gap between the satisfaction of psychological needs and the cultivation of high-quality ENG.

The significant positive influence of PE on BI (β=0.200, p=0.004) is congruent with the findings of Yuliani *et al*. [16], which identified PE as a principal determinant in the adoption of digital technologies. Within the MOOC context, this result indicates that learners will form an intention for continued use when they perceive that the platform will enhance their learning efficiency and academic outcomes. However, the relatively modest coefficient value (β=0.200) in comparison to other predictors may suggest a nuanced interpretation. In an era where MOOCs have become ubiquitous, learners may already possess a baseline expectation regarding the platform's utility. Consequently, while still a significant factor, PE may no longer function as a primary differentiator in the formation of BI, as its perceived benefits are now considered a standard feature rather than a novel advantage.

The insignificant influence of EE on BI (β=0.099, p=0.164) is noteworthy. Contrary to prior study by Permatasari *et al*. [17], who found EE to be a significant predictor of BI in mobile banking contexts, the present study found no such effect. This divergence may be attributed to the inherent accessibility of MOOCs, where learners already possess sufficient technological proficiency, making perceived ease of use a less salient factor in the formation of intention. Of greater theoretical significance is the finding that BI does not significantly predict PERS (β=0.143, p=0.063). This outcome directly challenges a foundational tenet of many technology acceptance models, which posit a direct and proximal link between intention and subsequent behavior. Contrary to Chiu and Wang [41], who found BI to be a significant predictor of web-based learning continuance, the present study reveals that in the gamified MOOC context, ENG quality supersedes intention as the primary driver of PERS. Several theoretical explanations may account for this finding. First, the gamified MOOC environment may create conditions where ENG becomes self-sustaining, rendering initial intention less relevant to continued participation. Second, the cross-sectional design may have captured a point in the learning trajectory where ENG had already displaced intention as the dominant behavioral driver. Third, the specific characteristics of the sample—experienced learners with substantial prior platform ENG—may have attenuated the intention–PERS relationship. This finding illustrates the well-documented intention–behavior gap in the learning context and highlights the role of ENG as the key mediating mechanism that converts motivational states into sustained learning behavior.

5. CONCLUSION

This study addressed a significant gap in MOOC research by developing and empirically validating an integrated UTAUT2–SDT–ENG model that explains the complex pathway from technology acceptance to learning persistence in gamified MOOC contexts. The study makes three original contributions. First, it provides the first empirical validation of a model that integrates UTAUT2 technology acceptance predictors, SDT-based psychological NS, and multidimensional student engagement within a single structural framework. Second, it demonstrates the existence of an intention–behavior gap in gamified MOOCs, showing that BI alone is insufficient to predict persistence. Third, it establishes student engagement as the primary driver of both BI and persistence, repositioning engagement as the central mechanism in MOOC persistence theory.

The theoretical contributions of this study are threefold. First, it demonstrates that student engagement—not BI—is the primary direct predictor of persistence, thereby challenging traditional technology acceptance paradigms and repositioning engagement as the central mechanism in MOOC persistence theory. Second, it establishes NS as the foundational mechanism that simultaneously drives HM and multidimensional engagement, confirming the central role of SDT in gamified learning contexts. Third, it reveals the intention–behavior gap in MOOCs, highlighting the necessity of engagement-focused interventions over intention-optimization strategies. Practically, the mechanism-driven gamification framework proposed here provides actionable design guidelines for MOOC developers: implementing learner-controlled progression to foster autonomy, adaptive challenges and meaningful feedback to build competence, and collaborative community features to nurture relatedness. This shift from superficial game elements to purposeful, need-supportive design is expected to cultivate sustainable engagement and reduce attrition rates.

Several limitations warrant consideration. The cross-sectional design precludes causal inference, and the purposive sample of 200 Thai MOOC learners may limit generalizability to other populations and non-gamified contexts. All constructs were measured via self-report, introducing susceptibility to CMB. Furthermore, the model omitted several UTAUT2 constructs (e.g., social influence, facilitating conditions, habit) and did not operationalize gamification intensity as a distinct variable, which may constrain predictive performance for HM and PERS. Future research should employ longitudinal designs, triangulate self-reported data with objective behavioral trace data (e.g., clickstream patterns, time-on-task), systematically decompose individual gamification elements, and replicate the model across diverse cultural contexts, MOOC platforms, and learner populations to establish the boundary conditions of the proposed framework.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest to report regarding the present study.

INFORMED CONSENT

Convenience sampling method was used for the online survey and only interested respondents filled the form, hence no separate consents were obtained from the individuals included in this study.

ETHICAL STAEMENT

The study was conducted using an anonymous online questionnaire. Participation was voluntary, and submission of the completed questionnaire was treated as informed consent. No personally identifiable information was collected, and all responses were analyzed in aggregate form.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Flagshare at https://doi.org/10.6084/m9.figshare.30520787.

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