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From Effort to Learning Expectations: How Habit Connects Technology Acceptance and Self-Regulated Learning in MOOCs

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Abstract

Higher education institutions now rely on MOOCs as a delivery channel for adult learners, lifelong learning, and SDG-4 commitments, yet the evaluation of MOOC effectiveness still leans on completion rates, satisfaction surveys, and platform analytics. These proxies say little about how learners actually experience the platform, or about the behavioural processes through which that experience feeds into expected outcomes. This study reconceptualises MOOC effectiveness from a learner-centred perspective and examines the behavioural pathway through which learners' perceptions of the platform translate into expected performance gains. We used a two-study design with independent cohorts. Study 1 developed and validated a learner-centred measurement instrument through expert content validation and exploratory factor analysis (n = 2,442). Study 2 used a two-wave design (n = 2,471) to test the relationships among the validated constructs in a structural model grounded in technology acceptance and self-regulated learning perspectives. Perceived effort expectancy influenced outcome performance expectancy roughly twice as strongly as learning process expectancy, indicating that ease of engagement matters more to learners' performance expectations than perceived pedagogical superiority of the format. Habitual learning behaviour was the behavioural mechanism through which both effort and process beliefs fed into outcome expectations. The findings shift MOOC effectiveness research in higher education away from platform features and completion rates and towards validated learner-centred constructs and the behavioural processes that produce sustained engagement. We draw implications for institutional evaluation practice, digital course design, and SDG-4 policy in developing-country higher education systems.

Introduction

The expansion of MOOCs since the post-pandemic period has reshaped the higher education access conversation, particularly in developing-country systems where lifelong learning, professional upskilling, and SDG-4 commitments now sit alongside the conventional undergraduate function of universities (Froehlich, 2023; Gamage et al., 2015). For higher education institutions, MOOCs are a routine delivery channel for adult learners that lies outside traditional enrolment categories. This raises an evaluation problem that the higher education research community has not yet resolved. Most assessments of MOOC effectiveness still rely on completion rates, satisfaction surveys, and platform-side analytics, and these proxies tell institutions very little about whether learners actually experience the platform as supportive of their performance, or about the behavioural processes through which that experience translates into expected outcomes (Carannante et al., 2021; Stracke, 2017). The gap matters because institutional investment in digital pedagogy, accreditation claims about quality of teaching and learning, and policy claims about SDG-4 progress are currently underwritten by metrics that do not capture the learner side of the equation.

Effectiveness in the literature is typically defined as meeting learner expectations, but many evaluations have historically relied on untested instruments, leaving a clear case for validated measures and evolving quality metrics (Gamage et al., 2015). At the learner level, well-established theories explain adoption and

persistence. The Technology Acceptance Model and UTAUT/UTAUT2 emphasise perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2012), while psychological perspectives such as self-determination theory and self-regulated learning point to motivation and strategic self-management as the drivers of engagement and outcomes (Gagné & Deci, 2005; Zimmerman, 2002).

Despite these advances, two gaps endure. First, a sizeable stream focuses on platform/pedagogy taxonomies and analytics without clarifying the behavioral mechanisms by which learners translate perceptions into durable engagement practices and outcome beliefs against the backdrop of persistent dropout and uneven completion (Carannante et al., 2021; Stracke, 2017). Second, in developing-country settings where MOOCs are positioned as levers for SDG-aligned inclusion, validated evidence on which learner-side perceptions and practices most influence perceived outcomes remains limited (Canaran & Bayram, 2024). Accordingly, we ask:

RQ1. What underlying, learner-centred factors characterize MOOC experiences?

RQ2. How do these factors relate to expected outcomes when theorized through established acceptance and learning frameworks (Davis, 1989; Gagné & Deci, 2005; Venkatesh et al., 2012; Zimmerman, 2002)*?*

In Study 1, we conduct expert-informed content validation and factor-analytic procedures to develop a defensible, learner-centred instrument (Gamage et al., 2015; Hair et al., 2019; Lynn, 1986; Tabachnick & Fidell, 2001). In Study 2, using the validated factors from Study 1 as empirical inputs, we theorize and test their relations through TAM/UTAUT2 and self-regulated learning perspectives, connecting learner perceptions and practices to expected outcomes in a developing-country MOOC context (Davis, 1989; Venkatesh et al., 2012; Zimmerman, 2002).

This study contributes to higher education research in two ways. We develop and validate a learner-centred measurement framework for evaluating MOOC effectiveness in adult higher education contexts, which allows the evaluation conversation to move past completion rates and platform analytics and towards constructs that capture how learners actually experience digital instruction. We then identify habitual learning behaviour as the behavioural mechanism through which learners' perceptions of effort and learning process translate into expected performance outcomes, speaking to a long-standing concern in the higher education literature about how institutions can design for sustained engagement rather than for initial enrolment.

Conceptual Background:

Engagement is a broad construct describing learners' involvement in educational activities. Engagement is typically examined through three dimensions, behavioural, emotional, and cognitive (Fredricks et al., 2004). Cognitive engagement represents the mental investment learners bring to their learning. In MOOCs, cognitive engagement matters most, because it is closely tied to learners' sense of participation

and their likelihood of completing the course. Learners who perceive MOOC content and learning experiences more positively are more likely to persist, complete courses, and obtain certification (Carannante et al., 2021).

Consistent with Self-Regulated Learning (SRL) theory (Zimmerman, 2002), learners are more likely to succeed in digital learning environments when they can actively regulate their cognition, motivation, and learning behaviours. Many institutions and MOOCs platforms provide source of information like engagement, level of attainment, participation and dropout rates, essential for Learning analytics. Despite such interventions and consequent rapid growth, there are aspects of MOOCs which may undermine their effectiveness, one such aspect is high drop-out rate.

Study 1: Scale Development and Construct Identification

Methods

Participants:

Study 1 drew on responses from 2,442 participants who were enrolled in and actively engaging with a Massive Open Online Course learning platform in 2023. The participants were drawn from an active cohort taking part in an ongoing training programme delivered on the platform, and each provided informed consent before completing the survey. Valid age data were available for 2,440 respondents, with two missing cases. Ages ranged from 19 to 67 years (M = 39.65, SD = 7.22). Gender was reported by all participants: 1,235 men (50.6 percent), 1,201 women (49.2 percent), and a small share (0.2 percent) who preferred not to disclose. About 40.2 percent had up to six years of experience, and the rest were spread across higher-experience categories, including a substantial group with more than 10 years of experience, which gave the sample a working balance of early-career, mid-career, and senior professionals.

Instrument Development Procedure:

This study used an exploratory instrument development design to build a survey measuring learner engagement and perceptions of MOOCs. Rather than fixing constructs upfront, we generated items from broad theoretical guidance in technology acceptance and learning theories. The Technology Acceptance Model (TAM; Davis, 1989) holds that perceived usefulness and perceived ease of use are the core determinants of users' technology adoption. We also drew on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2; (Venkatesh et al., 2012)), an extension of TAM that adds further predictors of technology use including habit.

Alongside these, we brought in constructs from educational psychology because they bear directly on online learning. We considered intrinsic motivation and extrinsic motivation, as defined in self-

determination theory (Gagné & Deci, 2005). We also included self-regulated learning (SRL) concepts (Zimmerman, 2002).

Stage 1: Item generation

We developed an initial pool of items by conducting a literature review of high-quality sources. We searched academic databases (Scopus and Web of Science) using keywords such as *"MOOC adoption," "technology acceptance," "online learning,"* and *"learner motivation."* Through this search and screening process, we identified key constructs and existing survey items used in prior studies of MOOCs and technology acceptance. Items capturing learners' cognitive engagement and study behaviours in MOOC settings including elaboration, organisation, and persistence, were adapted from the established self-regulated online learning measurement tradition (Jansen et al., 2017), while items reflecting performance and effort expectancy were informed by the UTAUT2 framework (Venkatesh et al., 2012). We synthesized these insights to formulate new survey statements tailored to the MOOC context. Each draft item was worded as a first-person statement about the learner's MOOC experience (e.g., "*Using the MOOC platform is easy for me*" reflecting perceived ease of use) so that respondents could rate their agreement on a Likert-type scale. In total, an initial set of approximately 48 items was generated, covering a broad range of themes related to technology perceptions, motivation, and engagement in MOOCs. No explicit subscales were imposed at this stage; instead, items were intentionally kept wide-ranging to allow underlying constructs to emerge in later analyses.

Stage 2: Expert Content Validation

We next subjected the draft instrument for content validation by a panel of experts. Eight experts in the fields of online learning, educational technology, instructional design, scale development, and psychometrics were recruited to review the item pool, a panel size above the minimum of six experts recommended for content validation studies (DeVellis, 1991). Inclusion criteria were a minimum of ten years of academic or applied experience in the relevant domain. We provided each expert with the list of items, the construct definitions, and the instrument's purpose. Using a 4-point rating scale (1 = "Not relevant," 2= "Somewhat relevant," 3= "Relevant," 4 = "Highly relevant"), experts independently rated each item's relevance to measuring learner engagement and perceptions of MOOCs. They also had opportunities to comment on wording clarity, ambiguity, or overlap between items.

We then quantified content validity using the Content Validity Index (CVI) method (Lynn, 1986; Polit & Beck, 2006; Cantrill et al., 1998). For each item, we computed the item-level CVI (I-CVI) as the proportion of experts giving a rating of 3 or 4 (indicating the item is content-relevant). Because I-CVI does not adjust to chance agreement, we additionally computed a modified Kappa statistics (k*) for each item following the procedure of Polit, Beck and Owen (2007). We also calculated the scale-level CVI, using the average method (S-CVI/Ave), as the mean of all I-CVI values across the 44-item set. In line with standard criteria, we sought I-CVI values of 0.78 or higher for each item and an S-CVI/Ave of 0.90 or higher for the overall

instrument to denote excellent content validity (Polit & Beck, 2006; Shi et al., 2012). Items that did not meet these thresholds or that received suggestions for improvement were revised or considered for removal. After the first round of ratings, nine items with borderline CVI scores were refined for clarity and then sent back to the experts for re-evaluation. This iterative review process ran for two rounds, by which point all experts agreed that the instrument had strong content relevance and clarity.

The outcome was a 44-item questionnaire ready for pilot testing. Expert evaluations confirmed that the instrument achieved robust content validity. In the final round, all items received high relevance ratings from the panel: each item's I-CVI sat well above the 0.78 benchmark (35 of 44 items reached I-CVI = 1.0, and the remaining 9 items reached I-CVI = 0.875; in rounded form, most items reached I-CVI = 1.0, with the lowest at 0.88). Item-level modified kappa values ran from 0.87 to 1.00, with all items in the excellent range ($k^* > 0.74$). The overall S-CVI/Ave for the 44-item scale came out to 0.97, comfortably above the 0.90 threshold typically cited for excellent content validity. On top of this, 79.5 percent (35 of 44) of the items attained unanimous agreement (all experts rated 3 or 4), giving a scale-level universal agreement index (S-CVI/UA) of 79.5 percent, which also meets the conventional criterion for high content validity (Polit & Beck, 2006).

During content validation, we made minor revisions to improve clarity and remove redundancy. From the initial pool of 48 items, one was found redundant, two were dropped as peripheral to the construct domain, and two were merged because experts flagged them as either overlapping with other items or slightly outside the focus of the construct. We retained 44 refined items in the instrument. Item generation drew on prior theory, but the latent dimensions were not fixed a priori; they were left to be recovered empirically through exploratory factor analysis in Stage 3.

Stage 3: Pilot Instrument Finalization

Results

We ran an exploratory factor analysis (EFA) using Principal Axis Factoring (PAF) with Oblimin rotation to identify the underlying constructs related to the use and perception of Massive Open Online Courses (MOOCs). PAF was chosen for its suitability with data carrying potential latent variables and its robustness to violations of normality. Oblimin rotation, which allows factors to correlate, was selected because correlated factors are common in social science data (Tabachnick & Fidell, 2001; Costello & Osborne, 2005).

Iteration Process

The factor analysis ran through multiple iterations before a clear structure settled. Items with low loadings and cross-loadings were identified and removed using a predetermined cut-off of .50 (Hair et al., 2019). We repeated the process until the solution stabilised. In the final iteration, the five-factor structure was stable and interpretable, with clearly delineated factors and significant loadings.

Kaiser-Meyer-Olkin (KMO) and Bartlett’s Test

The data were suitable for factor analysis. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy returned a value of .918, which is in the excellent range, and Bartlett's Test of Sphericity was significant (χ^2 (435) = 32475.351, $p < .001$), indicating sufficient correlation among the variables to support factor analysis (Field, 2018).

Factor Extraction and Factor Structure

Five factors were extracted on the basis of eigenvalues greater than one, following Kaiser's criterion (Kaiser, 1960). The pattern matrix produced distinct factors, labelled below on the basis of theoretical alignment and item coherence:

Habit (HA): Seven items with factor loadings ranging from 0.536 to 0.791. The items capture learners routinised cognitive engagement with MOOC content by combining sources, relating new information to prior knowledge, drawing on past experience, generating personal examples, and reading beyond the prescribed materials. These items were adapted from established self-regulated online learning measures in the MOOC literature (Jansen et al., 2017) where deep-learning and elaboration behaviours are treated as the cognitive expression of stable study habits in autonomous online environments.

Learning Process Expectancy (LPE): Included three items with factor loadings between 0.566 and 0.857. Items reflected perceptions about MOOCs' superiority over traditional classroom learning and online tests effectively judging participants' performance.

Perceived Platform Constraints (PPC): Comprised three items with loadings from 0.453 to 0.538, capturing perceived ineffectiveness of MOOCs in addressing queries, difficulty in clarifying doubts, and challenges posed by technical issues. The fifth factor that emerged from EFA, Perceived Platform Constraints, was carried forward to the measurement model assessment in Study 2 but did not meet the measurement-quality thresholds adopted in this study. Item loadings for the three indicators ranged from 0.453 to 0.538, which sits below the 0.70 indicator-reliability threshold recommended by Hair et al. (2019), and the resulting construct-level AVE fell below the 0.50 convergent-validity threshold. Retaining PPC on these values would have compromised the reflective measurement model, so the construct was removed before structural estimation.

Perceived Effort Expectancy (PEE): Included six items with factor loadings ranging from 0.585 to 0.892, reflecting the timely completion of assignments, adherence to program structure, and consistent engagement with provided materials.

Outcome Performance Expectancy (OPE): Seven items with factor loadings ranging from 0.433 to 0.687. These items captured expectations around skill enhancement, career effectiveness, and the perceived long-term benefits of MOOC participation.

Factor Correlations

Correlations among the extracted factors ran from negligible to moderate ranging from − 0.040 to 0.576 which is shown in Table 1. The factors are distinct, though they are not fully independent, with the strongest tie sitting between Habit and Perceived Effort Expectancy (r = .576).

The extracted factors show acceptable coherence and line up clearly with theoretical constructs relevant to MOOCs, which sets up the empirical and theoretical work that follows.

Table 1
Pattern Matrix

		Factor				
		HA	**LPE**	**PPC**	**PEE**	**OPE**
MC_34	When I am learning, I combine different sources of information (for example people, web sites, printed material)	.791				
MC_33	When I am learning online, I try to relate new information I find to what I already know	.723				
MC_35	I try to apply my previous experience when learning online	.714				
MC_31	I create my own examples to make information more meaningful while I am learning online	.708				
MC_32	I read beyond the core course materials provided in a MOOC programme to improve my understanding	.649				
MC_36	During learning online I treat the resources I find as a starting point and try to develop my own ideas from them	.605				
MC_30	When I study online, I make notes to help me organize my thoughts	.536				
MC_14	MOOCs cover the curriculum in a better way as compared to classroom teaching		.857			
MC_13	I think that MOOCs will help students learn better than classroom		.798			
MC_15	Online tests are a good judge of the performance of the participants in the course		.566			
MC_20	I feel that the instant-feedback tests in MOOCs are better than pen and paper tests					
MC_24	I feel that MOOCs are not effective in solving the queries of the participants			.538		
MC_16	It is difficult to get doubts clarified in a MOOC programme			.527		
MC_8	Technical glitches can make MOOC learning ineffective			.453		
MC_9	I prefer a MOOC programme on the basis of its ratings					
MC_10	I prefer a MOOC programme on the basis of the number of participants enrolled					

		Factor				
		HA	LPE	PPC	PEE	OPE
MC_7	Very good internet connectivity is a requisite for enrolling in a MOOC programme					
MC_40	I complete my assignments and activities on time				.892	
MC_44	I do not delay the submission of assignments and quizzes				.790	
MC_43	I watch videos in the way the programme is ordered				.682	
MC_42	I spend time on video tutorials available				.673	
MC_41	I browse through all the reading material available				.646	
MC_39	I remain active on all the days of the MOOC programme				.585	
MC_3	I enrol in MOOC programmes to add new skills					.687
MC_2	I enrol in MOOC programmes to enrich my knowledge					.656
MC_18	I feel MOOC programmes really enhance the skills of the participants					.479
MC_26	The learning that I undertake in MOOC programmes is very important to me					.459
MC_21	I think that specific MOOC programmes are effective for career development					.443
MC_19	I feel that time invested in MOOCs is really worth it					.437
MC_25	I think I will be able to use what I learn from the MOOC programmes in the future					.433
	Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.					
	a. Rotation converged in 8 iterations.					

Study 2

Theoretical Underpinning & Hypotheses development

Learning Process Expectancy describes the learner's belief that the MOOC format is superior to classroom instruction along dimensions such as flexibility, content depth, and assessment quality. Earlier work comparing online and classroom modes has found that learners differentiate between formats and form mode-level judgements that feed into their expectations of performance gains (Shen

et al., 2024). Recent evidence on digital learning platforms shows the same pattern, with perceived platform benefits associated with stronger learner expectations of academic gains (Hao et al., 2024; Zheng et al., 2025; Zhou et al., 2021). The UTAUT framework draws a similar line, where beliefs about a technology's capacity to improve outcomes raise performance expectations directly.

H1: Learning Process Expectancy (LPE) positively influences Outcome Performance Expectancy (OPE) in virtual learning environments.

Relationship between PEE and OPE

Perceived Effort Expectancy describes how effortless, simple, and intuitive learners find the use of online learning platforms. Earlier studies report PEE as one of the strongest predictors of learner behaviour, with learners more likely to engage in active learning when the effort required is reasonable and manageable (Tarhini et al., 2017; Zhou et al., 2021). Meta-analytic evidence supports the same conclusion at scale, identifying effort expectancy as one of the strongest predictors of behavioural intention in digital learning contexts (Zheng et al., 2025). At the same time, overly elaborate engagement strategies can raise cognitive load and reduce learning, which is why platform designs that minimise effort are typically the ones that perform best (Byers et al., 2024; Hao et al., 2024). Learners who find a platform simple to use and navigate are more likely to believe it will support their academic performance, because lower effort lowers cognitive barriers and raises trust in the system (Deng et al., 2023; Tarhini et al., 2017; Zimmerman, 2002).

Streamlined interfaces and uncluttered learning procedures are reported to raise expectations of academic advancement (Wei & Chou, 2020). Learning design quality, including instructional materials, evaluations, and workload, also shapes satisfaction (Eom et al., 2006; Kang & Im, 2013; Zheng et al., 2025).

H2: Perceived Effort Expectancy (PEE) positively influences Outcome Performance Expectancy (OPE) in virtual learning environments.

Relationship between LPE and OPE through Habit

Cigdem and Topcu (2015) showed that learners who engage in proactive virtual learning behaviours, including regular engagement, organisation of thoughts, and applied learning strategies, are more likely to expect better performance outcomes, since the routine itself is a signal of preparedness. Ease of use, social support, and learner-instructor interaction are repeatedly identified as conditions under which sustained engagement and habit formation take hold in online learning environments (Deng et al., 2023; Kang & Im, 2013; Zhou et al., 2021). The UTAUT account treats regular use as the basis for learners' belief that digital platforms will deliver learning results (Venkatesh et al., 2012), and self-regulated learning theory adds that learners who actively manage their materials show higher self-efficacy and academic performance (Zimmerman, 2002).

H3a: Habits (HA) mediate the relationship between Learning Process Expectancy (LPE) and Outcome Performance Expectancy (OPE).

Relationship between PEE and OPE through Habit

The UTAUT model holds that behavioural engagement and performance results are substantially shaped by perceived effort expectancy (Venkatesh et al., 2012). When learners find virtual platforms user-friendly, they are more likely to develop habits such as persistent resource exploration, timely task completion, and regular engagement, and these routine actions in turn reinforce their belief that the platform will improve their academic performance. Empirical work supports this sequence, with effort expectancy encouraging continuous platform use and continuous use feeding performance perceptions (Tarhini et al., 2017). The link between technological convenience and perceived academic performance runs through learners' behavioural participation rather than through the convenience itself. Evidence from VR-based orientation programmes adds a useful caveat, showing that high perceived involvement does not automatically translate into measurable learning improvements unless the method is built into learners' daily routine (Sadanala et al., 2025). Habit is therefore the behavioural channel through which perceived ease of use carries into outcome performance expectancy.

H3b: Habits (HA) mediate the relationship between Perceived Effort Expectancy (PEE) and Outcome Performance Expectancy (OPE).

Methods

Procedures

The academics who were part of a MOOCs program conducted in India were recruited for this survey in 2024. We adopted a two-wave rather than a three-wave time-lagged design because of the scale of the sample and the cycle of the MOOC programme. With over two thousand respondents in each wave, adding a third measurement window would have meant substantial attrition and respondent fatigue, and was not feasible inside the programme cycle. Two-wave designs of this kind are recognised in the mediation literature (Mitchell & Maxwell, 2013). Beyond the temporal separation, common method bias was further examined through full collinearity variance inflation factors estimated in SmartPLS following the procedure of Kock (2015). In this we measured the independent variables viz., learning process expectancy, perceived effort expectancy, and the mediator 'habit' at time T1. This was followed by measuring the dependent variable—outcome performance expectancy at time T2, which had a time lag of 15 days. This procedure was adopted to ward off issues arising from common method bias, and ensures temporal separation of the constructs under study (Jordan & Troth, 2020; Kock, 2015).

Participants

Study 1 and Study 2 drew on two independent cohorts of learners enrolled in the MOOC programme at different points in the programme cycle, with no respondent overlap across the two samples. This separation was a deliberate design choice. Running the exploratory factor analysis and the structural

model on the same respondents tends to inflate model fit. Drawing the Study 2 sample from a separate cohort allows the structural model to be tested on respondents who had no part in shaping the instrument, which is the practice recommended in the scale development literature (Hair et al., 2019). The two cohorts were also demographically comparable in age distribution, gender composition, and prior MOOC experience, so the measurement structure from Study 1 transfers reasonably to the Study 2 sample.

During the first wave we recruited n = 2581 participants for the study. The same set of respondents were contacted 15 days later to complete the wave 2. After final feasibility checks, i.e., respondents who participated in both the waves, an independent sample of n = 2,471 participants data was used for Study 2. Valid age information was available for 2,468 respondents, with three missing cases. Participants ranged in age from 22 to 63 years (M = 39.68, SD = 7.09). The sample included 1,244 men (50.3 percent) and 1,219 women (49.3 percent), with a small fraction (0.3 percent) opting not to disclose. Around 40.5 percent reported up to six years of experience, and the rest were spread across higher experience brackets, including a sizeable group with more than 10 years of experience. On prior exposure to MOOCs, most respondents (91.7 percent) reported having completed between zero and two MOOCs previously, so the sample was made up largely of learners with limited to moderate prior MOOC experience.

Measurement Model Assessment

We assessed the reflective measurement model against the standard guidelines in Hair et al. (2019). All items showed factor loadings above the 0.70 threshold, which is sufficient for indicator reliability. Composite reliability (CR) values ran from 0.789 to 0.869, comfortably past the 0.70 benchmark and supporting internal consistency reliability. Convergent validity was confirmed through average variance extracted (AVE) values, all of which sat above the 0.50 threshold across constructs. Discriminant validity was established through heterotrait-monotrait ratio (HTMT) values, which stayed below the conservative threshold of 0.85, confirming that each construct was empirically distinct.

The Habit construct in this study is operationalised through indicators of routinised cognitive engagement, including elaboration, integration with prior knowledge, and reading beyond prescribed materials, and not through the automaticity items typically used in the UTAUT2 tradition (Venkatesh et al., 2012). This follows the self-regulated online learning measurement tradition in the MOOC literature, where stable deep-processing and elaboration behaviours are treated as the cognitive expression of habit in autonomous online environments (Jansen et al., 2017). In adult MOOC settings, where the externally enforced routines of classroom learning are absent, this operationalisation captures the behavioural regularity that habit is meant to denote more closely than self-reported automaticity items developed for consumer-technology use.

The LPE construct is operationalised through three items that capture learners' comparative beliefs about MOOCs against classroom instruction, specifically the perceived curricular coverage of MOOCs, the perceived learning gains of MOOCs over classroom teaching, and the perceived adequacy of online assessment in judging participant performance. We retain the LPE label for continuity with the

technology acceptance literature on perceived value of online instruction (Shen et al., 2024), and read the construct accordingly in the discussion as a measure of learners' comparative belief in the format, not as a verdict on instructional design quality.

Table 2 indicate that Cronbach's alpha (CA) and composite reliability (CR) values for all constructs exceed the recommended threshold of 0.70, confirming satisfactory internal consistency and reliability. Furthermore, the AVE values range from 0.527 to 0.700, exceeding the minimum threshold of 0.50 and thereby establishing adequate convergent validity of all constructs. The HTMT values range from 0.166 to 0.701, remaining below the recommended threshold of 0.85, thereby confirming discriminant validity among all constructs. Similarly, the Fornell–Larcker criterion is satisfied, as the square roots of AVE (diagonal values) exceed the corresponding inter-construct correlations, providing further evidence of adequate discriminant validity. All the latent constructs are distinct with each other (Refer Table 3).

Table 2
Depicting reliability, and convergent validity

HA	**CA**	**CR**	**AVE**
	0.862	**0.866**	**0.549**
LPE	0.787	0.789	0.700
OPE	0.849	0.869	0.527
PEE	0.858	0.866	0.583

Source: SMART PLS-SEM output. Note: HA=Habit, LPE= Learning Process Expectancy, OPE= Outcome Performance Expectancy, PEE = Perceived Effort Expectancy, CR= Composite Reliability, CA= Cronbach Alpha, Average Variance Extracted (AVE)

Table 3
Discriminant validity (HTMT results)

HA	HA	LPE	OPE	PEE
LPE	0.319			
OPE	0.701	0.376		
PEE	0.616	0.166	0.644	
Fornell & Larcker				
	HA	**LPE**	**OPE**	**PEE**
HA	0.741			
LPE	0.266	0.837		
OPE	0.617	0.327	0.726	
PEE	0.541	0.147	0.568	0.764

Source: SMART PLS-SEM output. Note: HA=Habit, LPE= Learning Process Expectancy, OPE= Outcome Performance Expectancy, PEE = Perceived Effort Expectancy

Structural Model Assessment

We assessed collinearity in the structural model through variance inflation factor (VIF) analysis. VIF values for all predictors ranged between 1.34 and 2.81, significantly below the critical threshold of 3, indicating minimal risk of collinearity. The model explained 48.7% variance in Outcome Performance Expectancy (OPE) and 32.9% variance in Habit (HA), indicative of moderate predictive accuracy (Hair et al., 2019). We employed bootstrapping with 10000 subsamples to assess the significance of path coefficients. All hypothesized paths were significant ($p < .001$) (refer Table 4A and 4B). Specifically:

- Learning Process Expectancy (LPE) significantly influenced Outcome Performance Expectancy (OPE) ($\beta = 0.174, p < .001$), suggesting that positive perceptions of the learning process enhance learners' expected performance outcomes. (refer Fig. 1)
- Perceived Effort Expectancy (PEE) had the strongest effect on Outcome Performance Expectancy (OPE), ($\beta = 0.33$, $p < .001$), highlighting that perceived ease strongly boosts outcome performance expectancy. (refer Fig. 1)

The model revealed important mediated relationships. Habit (HA) significantly mediated the relationship between Learning Process Expectancy (LPE) and Outcome Performance Expectancy (OPE), as well as between Perceived Effort Expectancy (PEE) and Outcome Performance Expectancy (OPE), highlighting that habit acts as a crucial intermediate variable in translating learners' process perceptions and

perceived ease into outcome performance expectancy. Additionally, the predictive relevance of the structural model was validated by the Q^2 values obtained via blindfolding. All endogenous constructs exhibited Q^2 values above zero (refer Table 5), confirming adequate predictive relevance.

Table 4
A: Path coefficients

HA -> OPE	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.50%	97.50%	Addressing Hypotheses
	0.392	**0.392**	**0.02**	**19.517**	**0.000**	**0.352**	**0.431**	
LPE -> HA	0.191	0.191	0.018	10.441	0.000	0.154	0.226	
LPE -> OPE	0.174	0.174	0.016	10.791	0.000	0.142	0.206	H1 Supported
PEE -> HA	0.513	0.514	0.02	25.805	0.000	0.473	0.551	
PEE -> OPE	0.33	0.331	0.023	14.477	0.000	0.285	0.374	H2 Supported

Source: SMART PLS-SEM output

Table 4
B: Specific Indirect Effect

LPE -> HA -> OPE	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.50%	97.50%	Addressing Hypotheses
	0.075	**0.075**	**0.009**	**8.536**	**0.000**	**0.058**	**0.093**	**H3a Supported**
PEE -> HA -> OPE	0.201	0.201	0.012	16.475	0.000	0.179	0.226	H3b Supported

Source: SMART PLS-SEM output

Table 5
Prediction power analysis

Indicators	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
MC_30	0.166	1.123	0.84	1.121	0.83
MC_31	0.208	0.979	0.743	0.974	0.733
MC_32	0.146	1.253	0.936	1.246	0.928
MC_33	0.168	1.027	0.766	1.027	0.765
MC_34	0.147	1.113	0.809	1.107	0.808
MC_35	0.198	0.985	0.729	0.979	0.721
MC_36	0.209	0.919	0.712	0.911	0.702
MC_18	0.261	0.885	0.658	0.864	0.627
MC_19	0.176	1.002	0.68	1.000	0.674
MC_2	0.103	0.734	0.414	0.729	0.399
MC_21	0.220	0.83	0.626	0.818	0.604
MC_25	0.245	0.795	0.552	0.789	0.544
MC_26	0.292	0.733	0.52	0.727	0.504
MC_3	0.089	0.709	0.387	0.702	0.37

RMSE = Root mean square error, MAE = Mean absolute error, LM = Linear model

Discussion and Implication

This research study has two major findings. The first is methodological, where we developed the learner-centred items that were expert reviewed followed by exploratory factor analysis (EFA) and structured at four interpretable constructs, namely Habit, Learning Process Expectancy, Perceived Effort Expectancy, and Outcome Performance Expectancy. The fifth factor that emerged at EFA, viz., Perceived Platform Constraints, was dropped from the final structural model owing to below-recommended weights. The result is a compact instrument that captures how adult learners experience MOOCs without reducing them to completion rates or satisfaction scores.

The second finding is substantive. Perceived Effort Expectancy (β = .33) influences Outcome Performance Expectancy roughly twice as strongly as Learning Process Expectancy (β = .17). Both effects are partially carried by habitual learning behaviour, where the indirect path via Habit accounts for 38 per cent of the total PEE effect and 30 per cent of the total LPE effect.

The size gap between PEE and LPE is not what UTAUT2 predicts in the original consumer-technology samples, where performance expectancy is usually the stronger predictor and effort expectancy a secondary one (Venkatesh et al., 2012). Our pattern reverses this, and we consider three explanations worth taking seriously.

The first is sample-driven, in which our respondents are working adults with a mean age of about forty and most reporting more than six years of work experience. They are not undergraduates with free afternoons but people fitting study around jobs and families. For this group, ease of use is not a comfort feature but the difference between completing a module and abandoning it. The pattern may therefore not replicate in a sample of full-time students.

The second explanation is conceptual, where LPE in our instrument captures a comparative belief. It claims that MOOCs are pedagogically superior to classroom teaching, and that belief is harder to hold confidently. A learner can know that a platform is easy to navigate from a single session, whereas the same learner has to extrapolate from limited evidence to claim that the format itself is superior. Comparative judgements of this kind tend to be weaker predictors than first-hand experiential ones, and our pattern is consistent with that broader regularity.

The third explanation is mechanism-related. The mediation results show that LPE reaches OPE largely through Habit, and its direct path is the smaller of the two. This is what one would expect if process beliefs only translate into expected performance once the learner has stuck around long enough to build a routine. Effort beliefs do not require the same delay, which means that a learner can decide a platform is easy and update their performance expectations in the same sitting.

Theoretical Implications

The first implication concerns how higher education research measures MOOC effectiveness. Studies that read effectiveness off completion rates or end-of-course satisfaction miss the layer that actually predicts learner persistence, which is the learner's belief that the platform will improve their performance, situated upstream of the behaviour that produces that performance (Gamage et al., 2015; Stracke, 2017). A learner who expects no payoff will not stay, and a learner who expects payoff without building a routine will also not stay. The two failure modes look identical at the level of completion data and require different institutional responses. Higher education institutions designing evaluation frameworks for digital programmes need diagnostic instruments that can tell them apart, and the validated measurement structure offered here provides one route to that.

The second implication concerns the behavioural side of digital higher education. Recent meta-analytic work on UTAUT2 in digital learning has reported effort expectancy as one of the stronger predictors of behavioural intention (Zheng et al., 2025), although much of that evidence tracks intention rather than expected performance, and much of it pools learner populations without separating adult and working-professional learners from undergraduates. Our analysis extends that pattern one step ahead, from

behavioural intention to outcome expectation, and shows that the route is largely behavioural rather than cognitive. Habit operates as the conduit through which acceptance beliefs feed into expected gains, and it does so as a mediator rather than as a direct predictor. For adult-learner MOOCs in particular, treating habit only as a direct predictor of use behaviour, as the original UTAUT2 formulation does, leaves part of the system unexplained.

The third implication concerns the developing-country higher education context and the SDG-4 agenda. MOOCs are widely positioned in this literature as a delivery mechanism for SDG-4 commitments on quality education and equitable access, and for the lifelong learning agenda that increasingly defines higher education in countries with large working-adult populations (Canaran & Bayram, 2024; Froehlich, 2023). For this population, on the evidence here, ease of use is the primary lever through which perceived performance gains are formed, rather than the secondary usability concern that the digital pedagogy literature has typically treated it as. Higher education institutions and policymakers building MOOC infrastructure for SDG-4 inclusion would be better served, on this evidence, by reducing friction in the learner experience and by designing for routine engagement, than by adding pedagogical sophistication at the platform layer.

Practical Implications

First, ease before elaboration. If effort beliefs drive outcome expectations more than process beliefs, the design implication is to reduce friction at the navigation, login, and content-consumption layers before adding interactive features, gamification, or branching routes. Pedagogical sophistication that comes wrapped in interface complexity will pay back less than a simpler platform with the same instructional content. This runs against the common assumption that more sophisticated platforms generate more committed learners; in our data, the reverse is closer to the truth.

Second, design for routine, not for novelty. Because habit carries most of the effect of both beliefs, the levers that matter are the ones that build repeated, structured engagement: weekly cadence, predictable release schedules, reminder mechanisms, and small, recoverable assignments rather than large ones. Our findings suggest that novelty-driven design, is likely to work against the mechanism we are observing.

Third, evaluate the right thing. Institutions and policymakers benchmarking MOOC programmes against completion percentages are measuring an outcome that habit produces, not the perceptions and behaviours that drive habit. A validated learner-centred instrument of the kind we developed here gives evaluators the diagnostic resolution to see whether a programme is failing on effort perceptions, on process perceptions, or on the routine-building between them. The three problems require different interventions, and current evaluation practice cannot tell them apart.

Conclusion and Future research agenda

The study deems that improving usability and cultivating good learning habits are crucial for raising learners' performance expectations in digital environments. Perceived Effort Expectancy (PEE) appeared as the most impactful element than Learning Process Expectancy (LPE).

Apart from the individual efforts (personal engagement ‘Habit) collaborative or group behaviour especially in management education is vital to enhance the learning outcomes. To comprehend sustained engagement patterns future scholar may explore the longitudinal effect of learners towards digital learning method. Further can capture emotional aspects (such as digital self- efficacy, anxiety reduction and learning satisfaction) of engagement towards the digital learning. Further can implement and assess certain design modifications such as (gamification and AI-based learning assistance) to observe their effect on habit and outcome performance expectancy. Future work may also examine whether cultural norms, age, or past technological experience alter the relationship between anticipation factors, habits, and performance outcomes.

Declarations

Research statement

The authors confirm that this manuscript presents original work and has not been published or submitted elsewhere. The authors take full responsibility for the accuracy, integrity, and originality of the content and acknowledge that the manuscript is subject to editorial assessment, peer review, and any revisions requested by the editors and reviewers.

Conflict of interest:

None.

Consent to participate:

This is a survey-based study, and informed consent was obtained from all individual participants included in the study.

Ethics approval:

NA

Author Contribution

Dr. Vibhash Kumar (Conceptualization, Investigation, Validation, Writing – Original draft, Editing, and Reviewing), Dr. Komal Goyal (Conceptualization, Investigation, Methodology, Data collection, Formal analysis, Visualization, Writing – Original draft); Dr. Meenakshi Chaudhary (Editing, Reviewing, and Data Analysis)

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References

1. Byers RE, Carter CR, Wang Y (2024) Student engagement in synchronous online learning: Effectiveness of camera and chat/vote engagement methods. Decis Sci J Innovative Educ 22(3):138–157. https://doi.org/10.1111/dsji.12309
2. Canaran Ö, Bayram İ (2024) English language teacher trainers' capacity building in sustainable development goals through MOOCs. Int J Sustain High Educ 25(3):445–469
3. Cantrill JA, Sibbald B, Buetow S (1998) Indicators of the appropriateness of long term prescribing in general practice in the United Kingdom: Consensus development, face and content validity, feasibility, and reliability. Qual Health Care, *7*(3), Article 3.
4. Carannante M, Davino C, Vistocco D (2021) Modelling students' performance in MOOCs: A multivariate approach. Stud High Educ 46(11):2371–2386. https://doi.org/10.1080/03075079.2020.1723526
5. Cigdem H, Topcu A (2015) Predictors of instructors' behavioral intention to use learning management system: A Turkish vocational college example. Comput Hum Behav 52:22–28
6. Costello AB, Osborne JW (2005) Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Practical Assess Research Evaluation 10(7):1–9
7. Davis FD (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Q 13(3). Article 3. https://doi.org/10.2307/249008
8. Deng P, Chen B, Wang L (2023) Predicting students' continued intention to use E-learning platform for college English study: The mediating effect of E-satisfaction and habit. Front Psychol 14:1182980
9. DeVellis RF (1991) Scale development: Theory and applications. Sage Publications, Inc., p 121
10. Eom SB, Wen HJ, Ashill N (2006) The Determinants of Students' Perceived Learning Outcomes and Satisfaction in University Online Education: An Empirical Investigation*. Decis Sci J Innovative Educ 4(2):215–235. https://doi.org/10.1111/j.1540-4609.2006.00114.x
11. Froehlich DE (2023) Sustainable service-learning through massive open online courses. Sustainability 15(18):13522
12. Gagné M, Deci EL (2005) Self-determination theory and work motivation. J Organizational Behav, *26*(4), Article 4.
13. Gamage D, Fernando S, Perera I (2015) Quality of MOOCs: A review of literature on effectiveness and quality aspects. Media Comput, 6
14. Hair JF, Black WC, Babin BJ, Anderson RE (2019) *Multivariate data analysis* (8th ed.). Cengage

15. Hao Y, Zeng X, Yasin MAI, Boon Sim N (2024) Factors Influencing College Students' Learning Intention to Online Teaching Videos During the Pandemic in China. Sage Open 14(3). https://doi.org/10.1177/21582440241256769
16. Jansen RS, van Leeuwen A, Janssen J, Kester L, Kalz M (2017) Validation of the self-regulated online learning questionnaire. J Comput High Educ 29(1):6–27. https://doi.org/10.1007/s12528-016-9125-x
17. Jordan PJ, Troth AC (2020) Common method bias in applied settings: The dilemma of researching in organizations. Aust J Manage 45(1). Article 1. https://doi.org/10.1177/0312896219871976
18. Kang M, Im T (2013) Factors of learner–instructor interaction which predict perceived learning outcomes in online learning environment. J Comput Assist Learn 29(3):292–301. https://doi.org/10.1111/jcal.12005
19. Kock N (2015) Common method bias in PLS-SEM: A full collinearity assessment approach. Int J E-Collaboration 11:1–10. https://doi.org/10.4018/ijec.2015100101
20. Lynn MR (1986) Determination and Quantification Of Content Validity. Nurs Res 35(6):382
21. Mitchell MA, Maxwell SE (2013) A Comparison of the Cross-Sectional and Sequential Designs when Assessing Longitudinal Mediation. Multivar Behav Res 48(3):301–339. https://doi.org/10.1080/00273171.2013.784696
22. Polit DF, Beck CT (2006) The content validity index: Are you sure you know what's being reported? critique and recommendations. Research Nursing Health 29(5):489–497. https://doi.org/10.1002/nur.20147
23. Polit DF, Beck CT, Owen SV (2007) Is the CVI an acceptable indicator of content validity? Appraisal and recommendations. Research Nursing Health 30(4):459–467. https://doi.org/10.1002/nur.20199
24. Sadanala G, Xu X, He H, Bueno-Vesga J, Li S (2025) Enhancing distance learning with virtual reality: Investigating learners' engagement and outcomes. Distance Educ 46(2):225–252. https://doi.org/10.1080/01587919.2024.2351929
25. Shen J, Qi H, Mei R, Sun C (2024) A comparative study on the effectiveness of online and in-class team-based learning on student performance and perceptions in virtual simulation experiments. BMC Med Educ 24(1):135. https://doi.org/10.1186/s12909-024-05080-3
26. Shi J, Mo X, Sun Z (2012) [Content validity index in scale development]. *Zhong nan da xue xue bao Yi xue ban = Journal of Central South University. Medical sciences*, *37*(2), 152–155. https://doi.org/10.3969/j.issn.1672-7347.2012.02.007
27. Stracke CM (2017) The Quality of MOOCs: How to Improve the Design of Open Education and Online Courses for Learners? In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies. Novel Learning Ecosystems* (Vol. 10295, pp. 285–293). Springer. https://doi.org/10.1007/978-3-319-58509-3_23
28. Tabachnick BG, Fidell LS (2001) Using Multivariate Statistics, 4th edn. Allyn & Bacon
29. Tarhini A, Hone K, Liu X, Tarhini T (2017) Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: A structural equation modeling of

an extended technology acceptance model. Interact Learn Environ 25(3):306–328. https://doi.org/10.1080/10494820.2015.1122635

30. Venkatesh V, Thong JY, Xu X (2012) Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Q, 157–178
31. Wei H-C, Chou C (2020) Online learning performance and satisfaction: Do perceptions and readiness matter? Distance Educ 41(1):48–69. https://doi.org/10.1080/01587919.2020.1724768
32. Zheng H, Han F, Huang Y, Wu Y, Wu X (2025) Factors influencing behavioral intention to use e-learning in higher education during the COVID-19 pandemic: A meta-analytic review based on the UTAUT2 model. Educ Inform Technol 30(9):12015–12053. https://doi.org/10.1007/s10639-024-13299-2
33. Zhou S, Zhou Y, Zhu H (2021) Predicting Chinese University Students' E-Learning Acceptance and Self-Regulation in Online English Courses: Evidence From Emergency Remote Teaching (ERT) During COVID-19. Sage Open 11(4). https://doi.org/10.1177/21582440211061379
34. Zimmerman BJ (2002) Becoming a Self-Regulated Learner: An Overview. Theory Into Pract 41(2):64–70. https://doi.org/10.1207/s15430421tip4102_2

Figures

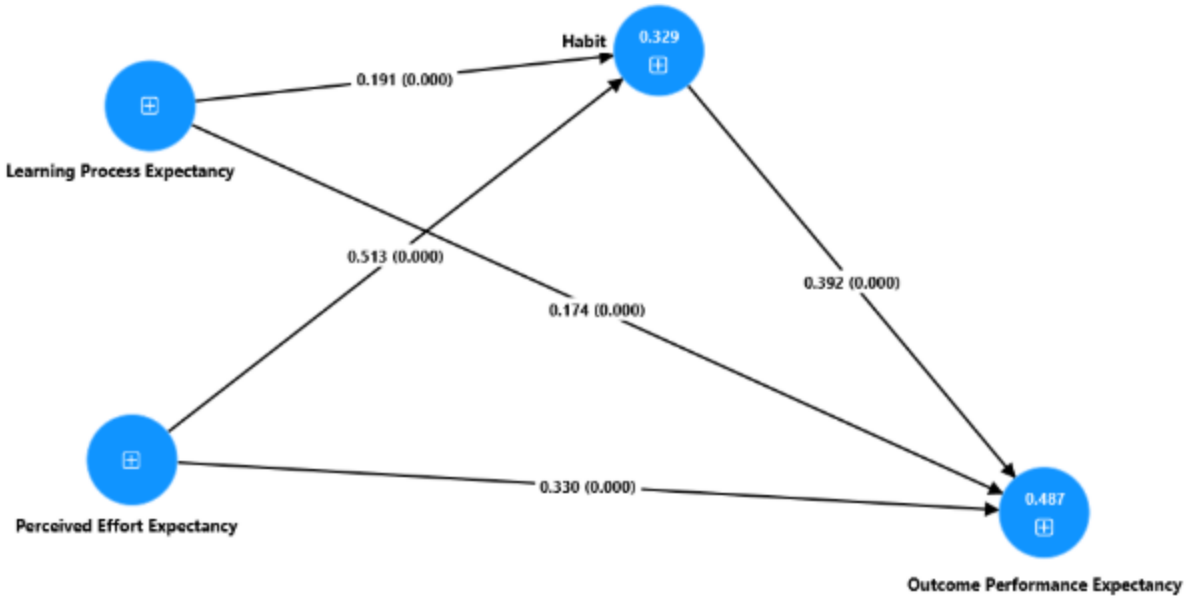


Figure 1

Structural model showing relationships among Learning Process Expectancy, Perceived Effort Expectancy, Habit, and Outcome Performance Expectancy