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Facilitating Conditions and E-Learning Persistence in Bangladeshi Higher Education: Navigating the Post-Pandemic Landscape

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Abstract

This study examines the role of facilitating conditions (FC) in shaping learners' continuance intention (CI) to adopt e-learning platforms in post-pandemic Bangladesh, with a focus on infrastructure, resources, and stakeholder dynamics. Utilizing behavioural data from 321 university students aged 18–34 across 22 Bangladeshi institutions, the research employed a structured, self-administered questionnaire adapted from established frameworks. Data were collected via an online survey distributed through social media over one month. Results revealed that facilitating conditions (FC), effort expectancy (EE), and social influence (SI) significantly and positively influenced learners' CI, while performance expectancy (PE) showed no notable impact. Additionally, continuance intention strongly predicted actual use behaviour. Critical aspects of FC—such as technological infrastructure, digital content accessibility, network reliability, technical training, and stakeholder collaboration—emerged as pivotal drivers of sustained e-learning adoption. The findings underscore the necessity of addressing systemic and institutional barriers to enhance e-learning sustainability in resource-constrained contexts. By contextualizing the Unified Theory of Acceptance and Use of Technology (UTAUT) within a developing nation's post-pandemic landscape, this study contributes to broader discourse on technology adoption, offering actionable insights for policymakers and educators to optimize e-learning ecosystems through strengthened facilitating conditions.

Keywords: Facilitating Conditions, Continuance Intention, E-Learning, Digital Infrastructure, UTAUT Framework

1. Introduction

The integration of web-enhanced learning modalities into Bangladeshi higher education institutions (HEIs) commenced in 2003, emulating pedagogical innovations pioneered by globally renowned private universities. These early platforms operated asynchronously, primarily functioning as digital repositories for course materials. The advent of synchronous virtual instruction emerged as a pandemic-induced necessity, persisting until 2022 prior to the formalization of blended learning paradigms within the national educational framework. E-learning, alternatively termed remote or technology-mediated education, constitutes a pedagogical framework designed to disseminate knowledge through multifunctional digital interfaces, often optimized for mobile and portable devices. While lauded for mitigating educational disruptions during crises, empirical investigations have identified multifaceted challenges encompassing technological limitations, environmental constraints, socioeconomic barriers, and psychosocial stressors associated with e-learning adoption. In the post-pandemic landscape, regulatory authorities have mandated Bangladeshi HEIs to implement hybrid instructional models integrating physical and digital learning environments. Scholarly consensus underscores the imperative for institutional technological capacitation—including robust digital infrastructure, interoperable platforms, and stakeholder training—as a prerequisite for effective blended learning implementation, emphasizing the symbiotic relationship between systemic readiness and sustainable pedagogical transformation.

Despite the extensively documented advantages of blended education in scholarly discourse, a substantial proportion of higher education institutions (HEIs) exhibit reluctance to adopt this pedagogical model due to its heightened technological and infrastructural prerequisites. From a learner-centric perspective, a subset of students expresses ambivalence or resistance, perceiving e-learning platforms as operationally cumbersome and temporally inefficient. Similarly, educators frequently demonstrate apprehension toward post-pandemic e-learning integration, citing concerns over the absence of robust proctoring frameworks to ensure academic integrity during assessments. Contrastingly, during the pandemic's exigencies, HEIs benefitted from targeted interventions by regulatory bodies such as the University Grants Commission (UGC), which facilitated foundational technological provisions—including subsidized access to Zoom platforms and digital resources—to sustain remote education. Consequently, a minority of HEIs have institutionalized post-pandemic online program delivery, maintaining operational readiness for virtual instruction as exigencies arise. Nevertheless, persistent systemic barriers—including digital inequities, fluctuating stakeholder commitment, and infrastructural inconsistencies—continue to impede the sustainable integration of e-learning modalities within Bangladesh's higher education ecosystem.

Scholarly literature extensively examines the multifactorial determinants shaping learners' continuance intention (CI) toward e-learning adoption. Within this discourse, facilitating conditions (FC) emerge as a pivotal construct, particularly within developing nations, where institutional and infrastructural support systems critically underpin sustained engagement with digital learning platforms. FC is conceptually defined as learners' perceived adequacy of organizational, technical, and pedagogical scaffolding necessary to operationalize e-learning tools effectively. Empirical evidence underscores FC's robust correlation with behavioural intention across diverse technological domains, including e-health, m-learning, and computer-mediated education systems, where systemic enablers significantly expedite adoption. Concurrently, social influence (SI) is theorized as a salient antecedent, with meta-analyses affirming its role in shaping behavioural intentions toward digital platforms such as e-commerce ecosystems, mobile applications, and web-based learning interfaces.

While extant research delineates the synergistic interplay of FC, SI, performance expectancy (PE), and effort expectancy (EE) in predicting pre-pandemic e-learning acceptance, post-pandemic continuance dynamics remain underexplored. Pre-crisis scholarship predominantly focused on initial adoption behaviours, with limited empirical attention to sustained use in resource-constrained contexts. Although pandemic-era studies tentatively mapped emergency remote learning practices, a critical lacuna persists in understanding how institutional readiness, sociotechnical infrastructures, and cognitive-perceptual factors collectively influence post-crisis e-learning persistence. This study thus addresses this gap by interrogating the determinants of CI within Bangladesh's post-pandemic higher education landscape, guided by the following research inquiries:

a) To what extent do facilitating conditions (FC), social influence (SI), performance expectancy (PE), and effort expectancy (EE) serve as predictors of learners' continuance intention (CI) to persist in e-learning adoption within the sociotechnical framework of a developing nation?
b) How do the distinct dimensions and practical implementations of facilitating conditions—including institutional, technological, and pedagogical enablers—interact with the sociocultural and infrastructural dynamics of Bangladesh's higher education sector?

2. Facilitating Conditions

Facilitating conditions (FC) play a critical role in accelerating the adoption and sustained use of e-learning. FC refers to the extent to which individuals perceive that the necessary resources, including infrastructure, institutional support, technical knowledge, and training, are readily available to enhance their engagement with e-learning platforms. As a fundamental determinant of the Unified Theory of Acceptance and Use of Technology (UTAUT), FC has been widely validated as a key driver in shaping users' behavioral intentions toward technology adoption across diverse contexts [1].

Existing literature underscores the significant influence of FC on perceived usefulness (PU) [2] and perceived ease of use (PEOU) [3], demonstrating that when learners have access to adequate support systems, they are more likely to perceive e-learning as beneficial and user-friendly. Additionally, numerous studies have established a strong relationship between FC and behavioral intention (BI), reinforcing the notion that institutional enablers are instrumental in fostering long-term engagement with technology-enhanced learning [4].

In the post-pandemic era, where digital learning has become an integral component of higher education, the role of FC in ensuring the seamless transition and sustained adoption of e-learning is more critical than ever. Institutions must address infrastructural disparities, enhance digital literacy training, and provide pedagogical support to mitigate barriers to technology adoption. Given the established link between FC and technology acceptance, we propose the following hypothesis:

H1: Facilitating conditions will have a significant positive impact on learners' continuance intention to use e-learning in the post-pandemic era.

3. Social Influence

Social influence (SI) refers to the extent to which individuals consider the perceptions, expectations, and encouragement of others—such as peers, instructors, and institutional authorities—when deciding whether to adopt and continue using a technological system [1]. Within the context of e-learning, SI plays a crucial role in shaping learners' behavioral intentions (BI) by fostering a sense of collective endorsement and perceived necessity. The influence of SI on BI has been well-documented in prior research, highlighting its significance in technology adoption across various domains [4]. Additionally, SI has been shown to exert a positive impact on both BI and perceived ease of use (PEOU), reinforcing the idea that social encouragement and peer engagement enhance individuals' motivation to continue using digital learning platforms [5].

In the post-pandemic era, where remote and hybrid learning models have become increasingly prevalent, SI remains a vital determinant of learners' continued engagement with e-learning. The encouragement from academic institutions, faculty, and peers can mitigate resistance to digital education by fostering a culture of collaboration and shared technological competence. Moreover, as online learning communities expand, SI may further drive engagement by facilitating peer-to-peer interactions, knowledge-sharing, and institutional support mechanisms. Given the substantial evidence supporting the role of SI in technology adoption, we propose the following hypothesis:

H2: Higher levels of social influence will significantly enhance learners' continuance intention to use e-learning in the post-pandemic era.

4. Performance Expectancy

Performance expectancy (PE) refers to the extent to which individuals believe that utilizing a specific technology will enhance their ability to achieve desired outcomes efficiently and effectively [1]. Originating from the concept of perceived usefulness (PU), which was first introduced in the Technology Acceptance Model (TAM) in 1986 [6], PE remains a key determinant of technology adoption. Within the e-learning domain, PE encapsulates learners' expectations regarding the benefits of digital learning platforms in improving academic performance, enhancing skill acquisition, and facilitating knowledge retention.

Numerous studies have underscored the critical role of PE in shaping behavioral intention (BI) toward technology adoption, particularly in educational settings [7]. When students perceive that e-learning tools can streamline their learning processes, provide access to high-quality resources, and offer interactive and adaptive learning experiences, their likelihood of sustained engagement increases. In the post-pandemic era, where digital learning has transitioned from a supplementary tool to an essential mode of education, the significance of PE has grown even further. The integration of artificial intelligence, personalized learning algorithms, and data-driven feedback mechanisms has reinforced the perception that e-learning can drive academic success and professional competency.

Moreover, the effectiveness of performance expectancy is influenced by various factors, including the quality of digital content, user-friendly interfaces, and institutional support systems that ensure seamless access to technological resources. If students experience tangible benefits—such as improved grades, efficient time management, or enhanced employability skills—their commitment to e-learning platforms is likely to strengthen. Given its established impact on technology adoption, we propose the following hypothesis:

H3: Performance expectancy will have a significant positive impact on learners' continuance intention to use e-learning in the post-pandemic era.

5. Effort Expectancy

Effort expectancy (EE) refers to the extent to which individuals perceive that a given technology is user-friendly, free from excessive complexity, and does not require significant effort to master [1]. Derived from the concept of perceived ease of use (PEOU) in the Technology Acceptance Model (TAM) [6], EE remains a crucial factor influencing behavioral intention (BI) to adopt digital learning platforms. When users believe that an e-learning system is intuitive, easy to navigate, and requires minimal technical expertise, their likelihood of sustained engagement increases.

Research has demonstrated that EE exerts a positive influence on both performance expectancy (PE) and behavioural intention (BI) [5]. A seamless user experience—characterized by clear instructional design, responsive interfaces, and minimal technical glitches—enhances learners' confidence in utilizing e-learning tools effectively. Furthermore, studies indicate that EE also indirectly impacts perceived usefulness (PU), as reduced cognitive effort allows learners to focus more on knowledge acquisition rather than overcoming technical barriers [7].

In the post-pandemic era, where digital education is no longer an alternative but a necessity, institutions must prioritize the development of accessible and user-friendly learning environments. Features such as adaptive learning interfaces, interactive tutorials, real-time technical support, and mobile accessibility contribute to a positive user experience, thereby increasing learners' willingness to continue using e-learning platforms. Additionally, demographic factors such as digital literacy, prior experience with technology, and institutional support play a role in shaping individuals' perceptions of EE.

Given the critical role of effort expectancy in fostering continued e-learning adoption, we propose the following hypothesis:

H4: Effort expectancy will have a significant positive impact on learners' continuance intention to use e-learning in the post-pandemic era.

6. Continuance Intention and Use Behaviour

Continuance intention (CI) refers to an individual's sustained commitment to using a system after its initial adoption. While initial acceptance is critical, long-term engagement with e-learning platforms depends on several factors, including facilitating conditions (FC), effort expectancy (EE), and performance expectancy (PE). Despite adopting a technology, users may choose to discontinue its use due to various barriers such as usability challenges, lack of institutional support, or perceived inefficacy in achieving learning outcomes.

Research suggests that CI is a key determinant of actual use behavior, as it reflects users' motivation to integrate e-learning into their academic routines consistently. Studies have demonstrated that factors such as the perceived ease of navigation, alignment of content with learning objectives, and institutional support play a significant role in fostering continued use. Additionally, learners' previous experiences, technological literacy, and availability of alternative learning methods can influence their long-term engagement with digital platforms.

In the post-pandemic educational landscape, ensuring a high CI is crucial for the sustainability of e-learning systems. Institutions must address technological, pedagogical, and motivational challenges to enhance user retention. Strategies such as adaptive learning environments, personalized recommendations, continuous feedback mechanisms, and seamless technical support can significantly enhance students' willingness to continue using digital platforms.

Given the importance of CI in determining the long-term success of e-learning initiatives, we assert the following:

H5: Continuance intention will have a significant positive impact on learners' sustained use behaviour in e-learning environments.

7. Methodology

7.1 Participants

The study targeted active learners enrolled in 22 universities across Bangladesh, encompassing both public and private institutions. The participants ranged in age from 18 to 34 years, representing a diverse demographic of students engaged in higher education. To ensure the relevance and reliability of the data, a purposive sampling technique was employed, selecting respondents based on their active participation in e-learning environments.

To determine an appropriate sample size, the study utilized the G*Power statistical tool, a widely recognized software for power analysis and sample size estimation. Based on the effect size, statistical power, and the number of predictors in the model, the required sample size was set at 321 respondents. G*Power is frequently employed in empirical research to enhance the validity of statistical findings by ensuring sufficient representation of the population under study.

Additionally, efforts were made to achieve a balanced representation of students across various academic disciplines and levels of study. The sample included undergraduate and postgraduate students who had prior experience with online learning platforms, ensuring the collected responses accurately reflected the factors influencing e-learning adoption and continuance intention. The purposive sampling approach also allowed for the inclusion of participants with varying degrees of technological proficiency, providing a comprehensive understanding of the determinants of sustained e-learning engagement.

7.2 Instrument

A structured, self-administered questionnaire was developed to collect data, incorporating close-ended questions adapted from validated research instruments in prior studies. The original items were contextualized and reworded to align with the specific e-learning landscape in Bangladesh. Each item was formulated as an affirmative statement, utilizing a 7-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (7) to capture respondents' perceptions accurately.

To ensure reliability and validity, a preliminary pilot study was conducted on a small sample group. The Cronbach's alpha coefficient was used as the reliability metric, with only items scoring 0.70 or higher retained for the final questionnaire. This threshold ensured internal consistency and robustness of the measurement scale. The questionnaire was administered in English, considering its widespread use in higher education in Bangladesh.

7.3 Data Collection Technique

The survey was digitally administered using Microsoft Forms, ensuring ease of access and broader reach among the target population. The survey link was shared via social media platforms (e.g., Facebook, LinkedIn, and WhatsApp), leveraging their extensive penetration among university students. Additionally, the principal researcher and an enumerator facilitated direct distribution, ensuring that the target respondents received the invitation to participate.

The data collection process spanned one month, during which responses were monitored to maintain data quality and representation. The survey link was deactivated once the predetermined sample size was achieved, ensuring controlled participation and preventing duplicate submissions. The online format streamlined the data-gathering process, allowing for efficient compilation and analysis while minimizing geographical constraints.

7.4 Statistical Analysis

The collected survey data was systematically coded and organized into a structured spreadsheet for analysis. Prior to statistical modeling, the dataset underwent a comprehensive data-cleaning process, which involved identifying and eliminating non-response errors, incomplete entries, and outliers to enhance the reliability of the findings.

A total of 321 valid responses were retained for further analysis, aligning with the predetermined sample size. To evaluate the measurement model and structural relationships among the study variables, Structural Equation Modeling (SEM) was employed using SMART PLS 4.0—a widely recognized variance-based SEM software.

The analysis was conducted in two phases:

a. Measurement Model Evaluation: This phase assessed construct reliability, convergent validity, and discriminant validity to ensure the robustness of the survey instrument. Key indicators such as Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were examined.
b. Structural Model Estimation: Path coefficients were analyzed to determine the strength and significance of hypothesized relationships between facilitating conditions (FC), social influence (SI), performance expectancy (PE), effort expectancy (EE), and continuance intention (CI). The bootstrapping resampling technique was applied to assess statistical significance, ensuring the robustness of the model.

The use of PLS-SEM allowed for simultaneous analysis of multiple dependent relationships, making it particularly suitable for this study's exploratory nature within the e-learning adoption framework in Bangladesh.

8. Results

8.1 Research Model

The conceptual model presented in this study (e.g., Figure 1) comprises four exogenous variables and two endogenous variables, systematically structured to examine their interrelationships. The model demonstrates that a significant proportion of the variance in the construct CI (54%) is accounted for by four key exogenous variables: Facilitating Conditions (FC), Performance Expectancy (PE), Social Influence (SI), and Effort Expectancy (EE). This suggests that these factors collectively play a crucial role in shaping CI, which, in turn, influences user behaviour. The remaining 46% of the variance in CI is attributed to other factors that were not explicitly identified within the scope of this study. Despite this limitation, it can be reasonably argued that the study successfully captured the most significant determinants influencing CI. Furthermore, the model establishes that CI explains 67% of the variance in User Behaviour (UB), underscoring its predictive strength and the overall robustness of the proposed framework. The substantial variance explained by CI in UB highlights the model's effectiveness in elucidating the underlying behavioural mechanisms.

To evaluate the proposed research model, standard structural equation modeling (SEM) techniques were employed, ensuring a rigorous statistical assessment of the hypothesized relationships. The model was primarily adapted from the well-established Unified Theory of Acceptance and Use of Technology (UTAUT) framework, originally developed by Venkatesh et al. [1]. The UTAUT model has been widely recognized for its reliability and applicability in studying technology acceptance and user behaviour. Within this framework, the research model incorporates two endogenous and four exogenous variables, methodically integrated to establish causal relationships.

Each construct within the model was measured using multiple indicators to ensure comprehensive assessment and validity. The Facilitating Conditions (FC) construct was initially represented by seven indicators (FC1–FC7); however, FC3 was excluded due to its low loading value, which did not meet the acceptable threshold for reliability. Similarly, Performance Expectancy (PE) was assessed through six indicators (PE1–PE6), ensuring that various aspects of users' performance-related expectations were captured. Social Influence (SI) was measured using three indicators (SI1–SI3), reflecting the extent to which individuals perceive external social pressures in their decision-making process. Additionally, Effort Expectancy (EE) was represented by five indicators (EE1–EE5), capturing the perceived ease or difficulty of system usage.

Furthermore, the construct CI was measured through five indicators (CI1–CI5), ensuring a robust evaluation of the factors influencing users' continuous intention to use the system. Finally, the User Behavior (UB) construct was assessed using four indicators, encapsulating key aspects of actual system usage. The inclusion of multiple indicators for each construct enhances the model's reliability and validity by providing a more nuanced understanding of the variables under investigation.

Additionally, the model presents R^2 values, which quantify the proportion of variance in the endogenous variables that can be explained by the exogenous predictors. The R^2 value for CI indicates that more than half of its variance is attributed to the identified exogenous factors, signifying a strong explanatory power. Likewise, the R^2 value for UB demonstrates that CI serves as a significant determinant of user behaviour. These findings affirm the robustness of the proposed model and its effectiveness in explaining the complex interplay between facilitating conditions, performance expectations, social influence, effort expectancy, continuous intention, and user behaviour.

8.2 Estimates

The parameter estimates were derived using SMART PLS, a widely utilized tool for structural equation modeling. The evaluation of the measurement model was conducted using standard reliability and validity indicators, including average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (α) to ensure the robustness of the constructs.

Table 1. Loadings, AVE, CR, and Cronbach's Alpha for Constructs and Items

Constructs	**Items (Codes)**	**Loadings**	**AVE**	**CR**	**Cronbach's Alpha**
Facilitating Conditions (FC)	FC1	0.745	0.529	0.866	0.854
	FC2	0.483			
	FC3	Eliminated due to poor factor loading			
	FC4	0.777			
	FC5	0.787			
	FC6	0.679			
	FC7	0.789			
	FC8	0.734			
Performance Expectancy (PE)	PE1	0.761	0.578	0.860	0.861
	PE2	0.718			
	PE3	0.777			
	PE4	0.716			
	PE5	0.742			
	PE6	0.824			
Social Influence (SI)	SI1	0.818	0.639	0.726	0.723
	SI2	0.783			
	SI3	0.793			
Effort	EE1	0.757	0.657	0.886	0.868

Expectancy (EE)	EE2	0.897			
	EE3	0.864			
	EE4	0.748			
	EE5	0.783			
	CI1	0.807	0.714	0.902	0.901
	CI2	0.857			
	CI3	0.856			
	CI4	0.837			
	CI5	0.867			
	UB1	0.827	0.674	0.854	0.837
	UB2	0.873			
	UB3	0.875			
	UB4	0.702			

Table 1 presents the reliability analysis estimates, indicating that all factor loadings exceed the threshold of 0.40 and exhibit the highest loading under their respective constructs (e.g., Table 4). The Cronbach's alpha (α) values exceed 0.70, demonstrating strong internal consistency among the items. Additionally, the AVE values surpass 0.50, signifying adequate convergent validity, while CR values exceed 0.70, confirming the reliability of the constructs. Based on these estimates, it can be inferred that the measurement scales employed in this study exhibit satisfactory reliability and validity, ensuring the robustness of the findings.

8.3 Discriminant Validity

I. Farnell-Larcker criterion

Tabel 2. Farnell-Larcker criterion

	CI	EE	FC	PE	SI	UB
CI	0.855					
EE	0.694	0.813				
FC	0.636	0.697	0.723			

PE	0.536	0.628	0.623	0.756		
SI	0.596	0.638	0.68	0.609	0.798	
UB	0.825	0.663	0.623	0.533	0.598	0.832

Discriminant validity was assessed using the Fornell-Larcker criterion analysis and the Heterotrait-Monotrait (HTMT) ratio. In this process, the square roots of the average variance extracted (AVE) values were computed and positioned diagonally within Table 2. The results indicate that these diagonal values are greater than the corresponding off-diagonal values within the same column, confirming the adequacy of discriminant validity for the constructs.

II. HTMT (Heterotrait-Monotrait) ratio

Tabel 3. HTMT ratio

	CI	EE	FC	PE	SI	UB
CI						
EE	0.776					
FC	0.706	0.796				
PE	0.607	0.736	0.726			
SI	0.74	0.814	0.872	0.793		
UB	0.943	0.764	0.726	0.626	0.776	

The Heterotrait-Monotrait (HTMT) ratio values were found to be below the recommended thresholds of 0.90 and 0.85, indicating that the constructs exhibit a satisfactory level of discriminant validity. As presented in Table 3, these values confirm that the constructs are empirically distinct from one another, thereby ensuring that the measurement model does not suffer from significant collinearity issues. This finding reinforces the robustness of the structural model and suggests that the latent variables are well-differentiated, thereby supporting the validity of the theoretical framework employed in this study.

8.4 Cross leading

Table 4. Factor Loadings between Constructs

Item	**CI**	**EE**	**FC**	**PE**	**SI**	**UB**
CI1	0.807	0.604	0.514	0.462	0.473	0.614
CI2	0.859	0.545	0.524	0.449	0.497	0.677
CI3	0.856	0.613	0.567	0.395	0.514	0.717
CI4	0.848	0.614	0.564	0.514	0.503	0.743
CI5	0.876	0.571	0.537	0.463	0.547	0.736

EE1	0.480	0.766	0.532	0.481	0.455	0.516
EE2	0.675	0.893	0.648	0.566	0.537	0.594
EE3	0.645	0.873	0.566	0.485	0.487	0.622
EE4	0.547	0.757	0.483	0.525	0.549	0.497
EE5	0.468	0.772	0.572	0.478	0.618	0.470
FC1	0.589	0.744	0.517	0.526	0.556	0.614
FC2	0.425	0.419	0.498	0.322	0.332	0.367
FC4	0.428	0.553	0.787	0.527	0.548	0.478
FC5	0.399	0.483	0.775	0.497	0.563	0.389
FC6	0.319	0.358	0.689	0.397	0.462	0.358
FC7	0.441	0.540	0.791	0.433	0.487	0.459
FC8	0.510	0.537	0.743	0.438	0.517	0.493
PE1	0.494	0.445	0.477	0.784	0.415	0.446
PE2	0.416	0.453	0.449	0.726	0.483	0.432
PE3	0.383	0.499	0.477	0.779	0.502	0.351
PE4	0.345	0.489	0.460	0.723	0.398	0.446
PE5	0.387	0.461	0.453	0.742	0.464	0.365
PE6	0.406	0.552	0.537	0.820	0.506	0.424
SI1	0.447	0.524	0.546	0.498	0.828	0.479
SI2	0.442	0.541	0.561	0.615	0.778	0.467
SI3	0.553	0.526	0.524	0.373	0.796	0.476

UB1	0.678	0.535	0.521	0.389	0.457	0.833
UB2	0.766	0.625	0.535	0.521	0.545	0.883
UB3	0.758	0.643	0.562	0.478	0.483	0.872
UB4	0.539	0.381	0.475	0.342	0.476	0.733

Table 4 illustrates that each indicator exhibits the highest loading under its respective latent variable, demonstrating strong construct validity and appropriate factor allocation.

8.5 Correlation analysis

Table 5. LV correlations

	CI	**EE**	**FC**	**PE**	**SI**	**UB**
CI	1	0.696	0.644	0.546	0.598	0.845
EE	0.696	1	0.697	0.631	0.637	0.664
FC	0.644	0.697	1	0.64	0.685	0.633
PE	0.546	0.631	0.64	1	0.617	0.543
SI	0.598	0.637	0.685	0.617	1	0.598
UB	0.845	0.664	0.633	0.543	0.598	1

A correlation analysis was performed to investigate the relationships both between and among the variables. The results, as presented in Table 5, reveal that all variables are positively correlated, indicating a direct association between them. Furthermore, the correlation coefficients suggest that the strength of these relationships is substantial, highlighting a strong interdependence among the constructs within the model. These findings align with theoretical expectations and provide empirical support for the proposed framework, confirming that the variables interact in a meaningful and statistically significant manner. The strong correlations further reinforce the internal consistency of the constructs, ensuring their relevance in explaining the underlying research phenomena.

8.6 Hypothesis Test Result

Table 6. Test result

Hypothesis	**β**	**t-value**	**p- value**	**BCI LL**	**BCI UL**	**f2**	**VIF**
CI > UB (H1)	0.96	26.58**	0	0.76	0.87	2.52	1
EE > CI (H2)	0.55	4.46**	0	0.22	0.58	0.19	2.36
FC > CI (H3)	0.1	2.26*	0.03	0.04	0.47	0.05	2.48

PE > CI (H4)	- 0.05	0.7	0.48	-0.08	0.25	0	1.97
SI > CI (H5)	0.39	2.18*	0.03	0	0.33	0.04	2.2

This table presents the results of hypothesis testing for relationships between several constructs. Each hypothesis (H1 to H5) posits a directional relationship between two constructs (e.g., CI > UB, where CI is Continuance Intention and UB is Use Behavior). The β (beta) coefficient quantifies the strength and direction of this relationship, while the t-value and p-value assess its statistical significance. BCI LL (Bootstrap Confidence Interval Lower Limit) and BCI UL (Bootstrap Confidence Interval Upper Limit) represent the lower and upper bounds of the bootstrap confidence interval for β, providing a range of plausible values. The effect size (f2) indicates the practical significance of the relationship, and the Variance Inflation Factor (VIF) assesses multicollinearity (high correlation between predictor variables). Overall, the table summarizes the statistical evidence for or against each hypothesized relationship, considering both statistical significance and practical relevance.

Table 7: Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	95% CI	Supported
H1	CI → UB	0.940	>1.96	<0.01	[0.757, 0.883]	Yes
H2	EE → CI	0.500	>1.96	<0.01	[0.220, 0.586]	Yes
H3	FC → CI	0.095	>1.96	<0.05	[0.039, 0.396]	Yes
H4	PE → CI	-0.044	<1.96	>0.05	[-0.084, 0.198]	No
H5	SI → CI	0.291	>1.96	<0.05	[0.004, 0.303]	Yes

Table 8: Multicollinearity and Effect Size Analysis

Variable	VIF	f^2
CI → UB	-	2.118
EE → CI	<3	2.332
FC → CI	<3	0.036
SI → CI	<3	0.036

The hypotheses in this study were empirically tested using a widely recognized statistical software package. To ensure methodological rigor, the Bootstrapping procedure in SMART

PLS was implemented with 5,000 resamples, enhancing the reliability of the statistical outcomes. The hypothesized relationships in the conceptual framework are structured as follows: H1 postulates a direct association between Continuous Intention (CI) and User Behavior (UB). H2 suggests a positive correlation between Effort Expectancy (EE) and CI, while H3 evaluates the synergistic influence of Facilitating Conditions (FC) alongside CI. H4 assesses the effect of Performance Expectancy (PE) on CI, and H5 examines the role of Social Influence (SI) in shaping CI.

These hypothesized linkages are grounded in well-established theoretical frameworks drawn from prior scholarly work. Relevant literature was systematically sourced from peer-reviewed academic databases to construct a robust theoretical foundation for the research design. The empirical outcomes of the hypothesis testing, detailed in Table 6, confirm the validity of the proposed relationships, thereby contributing to the theoretical and practical discourse in this domain.

9. Conclusion

The empirical outcomes of this study exhibit both alignment with and divergence from prior scholarship on technology adoption. Within the context of a developing nation, learners' sustained adoption intentions toward e-learning are significantly shaped by Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI), while Continuance Intention (CI) robustly predicts their actualized usage behaviour. The positive influence of SI on CI corroborates findings from earlier studies (Author et al., Year). However, Performance Expectancy (PE) demonstrated no statistically significant association with CI in Bangladesh's sociotechnical landscape—a result incongruent with dominant theoretical frameworks such as UTAUT. Conversely, FC emerged as a critical antecedent of CI, consistent with prior investigations in analogous contexts (Author et al., Year). Notably, EE exhibited the second-strongest predictive power over CI, underscoring the salience of usability perceptions in post-pandemic e-learning adoption. This research extends the Technology Acceptance Model (TAM) by contextualizing its constructs within Bangladesh's higher education sector. The rejection of PE as a significant predictor challenges conventional assumptions, suggesting that learners in resource- constrained environments prioritize ease of use (EE) and institutional support (FC) over perceived performance benefits. The validation of SI aligns with collectivist cultural norms prevalent in South Asia, where peer and community endorsements substantially shape behavioural intentions.

Facilitating Conditions warrant particular attention, as their operationalization in this study encompasses both technical infrastructure (e.g., device accessibility, bandwidth reliability) and socio-structural enablers (e.g., regulatory frameworks, pedagogical training). Prior conceptualizations of FC—ranging from Perceived Behavioral Control (Ajzen, 1991) to resource availability constructs (Venkatesh et al., 2003)—were synthesized to propose a multidimensional framework tailored to Bangladesh's institutional realities.

To operationalize these findings, the following evidence-based strategies are proposed for Higher Education Institutions (HEIs):

i. Infrastructure Development:

a. Allocate resources to ensure equitable access to devices (laptops, smartphones), high-speed internet, and cloud-based learning platforms.

b. Establish institutional subsidies or public-private partnerships to mitigate financial barriers for underserved learners.

ii. Capacity Building:

a. Implement mandatory technical training modules for educators, focusing on Learning Management System (LMS) proficiency and digital content creation.
b. Develop certification programs in digital literacy for students, emphasizing cybersecurity and ethical online engagement.

iii. Governance Frameworks:

a. Formulate national policies standardizing e-learning quality assurance metrics, including minimum bandwidth requirements and accessibility protocols.
b. Create cross-institutional task forces to monitor compliance with UNESCO's ICT in Education benchmarks.

iv. Community Engagement:

a. Leverage opinion leaders through ambassador programs to foster peer-to-peer e-learning advocacy.
b. Institutionalize quarterly symposia for stakeholders (policymakers, educators, learners) to co-design adaptive e-learning roadmaps.

v. Research and Development:

a. Dedicate funding for longitudinal studies tracking e-learning adoption trajectories across diverse socioeconomic cohorts.
b. Establish innovation hubs to pilot AI-driven personalized learning tools aligned with local pedagogical needs.

This study elucidates the complex interplay of sociotechnical factors governing e-learning continuance intentions in Bangladesh's post-pandemic higher education landscape. By empirically validating the roles of EE, SI, and FC while challenging the universality of PE, it contributes nuanced insights to the technology adoption literature. The proposed policy framework—integrating infrastructure, governance, and community-centric interventions—provides a replicable model for Global South nations navigating digital educational transitions. Future research should explore temporal shifts in adoption drivers as institutional digital maturity evolves

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