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Fostering Continuous Intention to Use E-learning Platforms among Students of Open Online Flexible Distance Learning Higher Education Institutions

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Abstract

This study investigates the determinants influencing students' continuous intention to use e-learning platforms in open online flexible higher education institutions. The aim is to examine the roles of effort expectancy, facilitating conditions, and performance expectancy in shaping students' engagement with e-learning platforms and the mediating effects of e-satisfaction and learning self-efficacy. A sample of 377 students from open online flexible higher education institutions participated in the study. The methodology followed the guidelines for structural equation modeling (SEM) analysis. Data were collected using a Likert scale questionnaire and analyzed using Partial Least Squares (PLS) method. Smartpls4 was utilized to analyze the data. The findings reveal that effort expectancy, facilitating conditions, and performance expectancy significantly influence students' continuous intention to use e-learning platforms. Additionally, e-satisfaction and learning self-efficacy mediate the relationships between these determinants and continuous intention to use. Specifically, user-friendly interfaces, comprehensive support services, and the perceived usefulness of e-learning platforms contribute to students' intention to engage with the platform continuously. The study also highlights the relevance of theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) in understanding technology adoption and usage behavior in higher education. The study's implications suggest that institutions should focus on enhancing usability, providing support services, and demonstrating the practical benefits of e-learning platforms to foster students' engagement and satisfaction. These findings offer practical guidance for institutions seeking to optimize

their online learning environments and improve students' learning experiences in open online flexible higher education settings.
Keywords: Effort Expectancy, Facilitating Conditions, Performance Expectancy, E-Satisfaction, Learning Self-Efficacy, Continuous Intention to Use

Introduction

E-learning platforms revolutionize higher education with open, flexible, and global distance learning opportunities. They offer diverse courses, accommodating varied schedules and needs, fostering inclusive education by breaking geographical barriers (Al-Hawamleh, 2024). These platforms promote lifelong learning, enabling self-paced upskilling. Facilitating collaboration, enhance learning experiences for students and instructors (Saeed Al-Maroof et al., 2020). Recent advancements focus on user engagement, integrating AI for personalized learning, gamification for active participation, and adaptive algorithms for real-time feedback (Ahmad et al., 2023). Collaborative tools simulate traditional classroom environments (Deshpande et al., 2024). These innovations underscore institutions' commitment to continually improving E-learning platforms, ensuring quality education's accessibility and relevance in the digital age (Bushra & Devi, 2023). In Malaysia, E-learning platforms for open online flexible distance learning in higher education institutions have witnessed significant strides. Institutions are leveraging advanced technologies like virtual reality (VR) and augmented reality (AR) to create immersive learning experiences (Ramasamy et al., 2023). Tailored content delivery systems based on learners' preferences and progress are being implemented, enhancing engagement and comprehension (Jing et al., 2024). Moreover, mobile learning apps are gaining traction, providing on-the-go access to educational resources (Anthony, 2024). Collaborative tools integrated with social media platforms facilitate interaction among students and instructors, fostering a sense of community in virtual classrooms. These innovations highlight Malaysia's commitment to harnessing technology for accessible and quality higher education (Looi et al., 2022). The challenge of sustaining the intention to use E-learning platforms in Malaysian open online flexible distance learning higher education institutions lies in addressing barriers to adoption and engagement. Issues such as limited internet connectivity in rural areas, digital literacy disparities, and cultural preferences for traditional learning methods hinder widespread acceptance (Huda, 2024). Moreover, concerns regarding the effectiveness of online education compared to face-to-face instruction persist among students and educators (Khan et al., 2023). Ensuring ongoing support, training, and technological infrastructure investment are essential to cultivate trust and motivation among users (Tewari et al., 2023). Additionally, fostering a conducive online learning environment that promotes interaction, feedback, and personalized support can bolster long-term engagement with E-learning platforms (Al Arif et. al, 2024). Understanding the intention to continuously use E-learning platforms in Malaysian higher education institutions is crucial for policymakers, institutions, students, and academics alike. For policymakers, insights can inform policies to enhance digital infrastructure and address digital literacy gaps, fostering equitable access to education. Institutions can tailor platform features to meet user needs, promoting engagement and retention. Students benefit from improved learning experiences and access to quality education, empowering lifelong learning. Academics can refine teaching strategies based on user preferences and feedback, optimizing online pedagogy. Ultimately, studying the intention to continuously use E-learning platforms ensures informed decision-making and drives advancements in online education, benefiting all stakeholders. This study aims to assess the direct and indirect relationship between performance expectancy, effort expectancy, and facilitating conditions with the continuous intention to use the e-learning platform with the learning self-efficacy and e-satisfaction as the mediators among the students in open online flexible higher education institutions.

Literature Review

Underpinning Theory

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) serves as an ideal theoretical framework for studying the direct and indirect relationships between performance expectancy, effort expectancy, facilitating conditions, continuous intention to use e-learning platforms, and the mediating factors of learning self-efficacy and e-satisfaction among students in open online flexible higher education institutions. Within UTAUT, performance expectancy refers to users' beliefs regarding the benefits and usefulness they anticipate from adopting a particular technology, such as e-learning platforms. Effort expectancy pertains to users' perceptions of the ease of use and simplicity associated with interacting with the technology. Facilitating conditions encompass the external factors, including organizational and technical support, that can influence users' adoption and usage behavior. In the context of open online flexible higher education institutions, where students often rely heavily on digital resources for learning, these determinants play a crucial role in shaping students' intentions to continue using e-learning platforms. Moreover, UTAUT allows for the inclusion of mediators, such as learning self-efficacy and e-satisfaction, which can further elucidate the mechanisms through which the determinants influence users' behavioral intentions. Learning self-efficacy reflects students' confidence in their ability to utilize the e-learning platform effectively to achieve their academic goals, while e-satisfaction captures students' overall satisfaction with their learning experiences. By employing UTAUT as the underpinning theory, researchers can comprehensively explore how performance expectancy, effort expectancy, and facilitating conditions, directly and indirectly, influence students' continuous intention to use e-learning platforms, mediated by learning self-efficacy and e-satisfaction, in the unique context of open online flexible higher education institutions.

Relationship between Effort Expectancy, Satisfaction, Learning Self-Efficacy and Continuous Intention to Use

Effort expectancy, as a crucial component of the Unified Theory of Acceptance and Use of Technology (UTAUT), plays a pivotal role in shaping users' intentions to continue using e-learning platforms. In the context of higher education institutions, where students are increasingly reliant on digital tools for learning, understanding the dynamics between effort expectancy, satisfaction, learning self-efficacy, and continuous intention to use is paramount. Effort expectancy refers to the perceived ease of use and the level of effort required to operate a technology (Deng et al., 2023). When students perceive e-learning platforms as easy to navigate and comprehend, they are more inclined to engage with them consistently. This positive perception of effort expectancy directly influences their continuous intention to use the platform (Rankapola & Zuya, 2023). Moreover, satisfaction acts as a mediator in this relationship. When students find the e-learning platform user-friendly and efficient, they are more likely to derive satisfaction from their learning experiences. This satisfaction, in turn, reinforces their intention to continue using the platform (Dash et al., 2022). Additionally, learning self-efficacy serves as another crucial mediator. As students become more proficient in utilizing the e-learning platform and experience success in their learning endeavors, their confidence in their ability to master the platform and achieve academic goals grows (Khera, 2024). This enhanced self-efficacy further strengthens their intention to persist in using the platform. The relationship between effort expectancy, satisfaction, learning self-efficacy, and continuous intention to use the e-learning platform forms a complex interplay wherein positive perceptions of ease of use, satisfaction with the platform, and confidence in one's learning abilities synergistically contribute to sustained engagement with digital learning resources in higher education settings (Ye et al., 2022). Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between effort expectancy and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H2: There is a relationship between effort expectancy and e-satisfaction in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H3: There is a relationship between effort expectancy and learning self-efficacy in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H4: There is a mediating effect of e-satisfaction on the relationship between effort expectancy and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H5: There is a mediating effect of learning self-efficacy on the relationship between effort expectancy and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

Relationship between Facilitating Conditions, Satisfaction, Learning Self-Efficacy and Continuous Intention to Use

Facilitating conditions represent the extent to which students perceive the availability of resources, support, and technical infrastructure necessary to effectively utilize e-learning platforms in higher education (Khera, 2024). Understanding the relationship between facilitating conditions and continuous intention to use, with satisfaction and learning self-efficacy as mediators, sheds light on the complexities of digital learning environments. In higher education institutions, students' perceptions of facilitating conditions significantly influence their intentions to persist in using e-learning platforms (Alyoussef & Omer, 2023). When students perceive ample technical support, access to necessary resources, and a conducive learning environment, they are more likely to continue engaging with the platform over time (Zheng et al., 2023). Satisfaction serves as a mediator in this relationship. When students have access to facilitating conditions, they are more likely to experience satisfaction with their learning experiences. This satisfaction, stemming from a smooth and well-supported learning process, reinforces their intention to continue using the platform (Gurban & Almogren, 2022). Similarly, learning self-efficacy acts as another crucial mediator. As students encounter fewer barriers related to technical issues or resource constraints, they develop a stronger belief in their ability to succeed in their learning endeavors. This heightened self-efficacy, in turn, motivates them to persist in using the e-learning platform (Wang, 2023). The relationship between facilitating conditions, satisfaction, learning self-efficacy, and continuous intention to use the e-learning platform underscores the importance of providing students with the necessary support and resources to facilitate their engagement with digital learning (Tawafak et al., 2023). By addressing facilitating conditions, institutions can enhance students' satisfaction and confidence in their learning abilities, ultimately fostering a more sustainable and effective e-learning environment in higher education (Al Amin et al., 2023). Thus, the following hypotheses were proposed for this study:

H6: There is a relationship between facilitating conditions and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H7: There is a relationship between facilitating conditions and e-satisfaction in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H8: There is a relationship between facilitating conditions and learning self-efficacy in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H9: There is a mediating effect of e-satisfaction on the relationship between facilitating conditions and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H10: There is a mediating effect of learning self-efficacy on the relationship between facilitating conditions and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

Relationship between Performance Expectancy, Satisfaction, Learning Self-Efficacy and Continuous Intention to Use

Performance expectancy, a key component of the Unified Theory of Acceptance and Use of Technology (UTAUT), reflects students' perceptions of how effective an e-learning platform will be in enhancing their learning outcomes (Tawafak et al., 2023). Understanding the relationship between performance expectancy and continuous intention to use, with satisfaction and learning self-efficacy as mediators, is essential in elucidating the dynamics of student engagement in digital learning environments within higher education institutions (Khera, 2024). In higher education, students' perceptions of the potential benefits and effectiveness of an e-learning platform strongly influence their intention to continue using it (Wang, 2023). When students believe that the platform will help them achieve their academic goals, enhance their learning experiences, and improve their performance, they are more likely to maintain their engagement with it over time. Satisfaction serves as a mediator in this relationship (Osei et al., 2022). As students perceive the e-learning platform as effective in meeting their learning needs and facilitating their academic progress, they experience satisfaction with their overall learning experiences. This satisfaction, in turn, reinforces their intention to persist in using the platform (Xu & Qiu, 2021). Similarly, learning self-efficacy acts as another crucial mediator. As students perceive the e-learning platform as conducive to their learning and academic success, they develop a stronger belief in their ability to effectively utilize the platform to achieve their educational objectives (Zeng & Cleesuntom, 2024). This increased self-efficacy motivates them to continue engaging with the platform. The relationship between performance expectancy, satisfaction, learning self-efficacy, and continuous intention to use the e-learning platform underscores the importance of designing platforms that are perceived as effective and beneficial by students (Chen et al., 2021). By enhancing students' perceptions of performance expectancy, institutions can foster satisfaction and confidence in their learning abilities, ultimately promoting sustained engagement with digital learning resources in higher education (Younas et al., 2022). Hence, the following hypotheses were proposed for this study:

H11: There is a relationship between performance expectancy and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H12: There is a relationship between performance expectancy and e-satisfaction in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H13: There is a relationship between performance expectancy and learning self-efficacy in the continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H14: There is a relationship between e-satisfaction and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H15: There is a relationship between learning self-efficacy and continuous intention to use e-learning platform among students in open online flexible higher education institutions.

H16: There is a mediating effect of e-satisfaction on the relationship between performance expectancy and continuous intention to use the e-learning platform among students in open online flexible higher education institutions.

H17: There is a mediating effect of learning self-efficacy on the relationship between performance expectancy and continuous intention to use the e-learning platform among students in open online flexible higher education institutions.

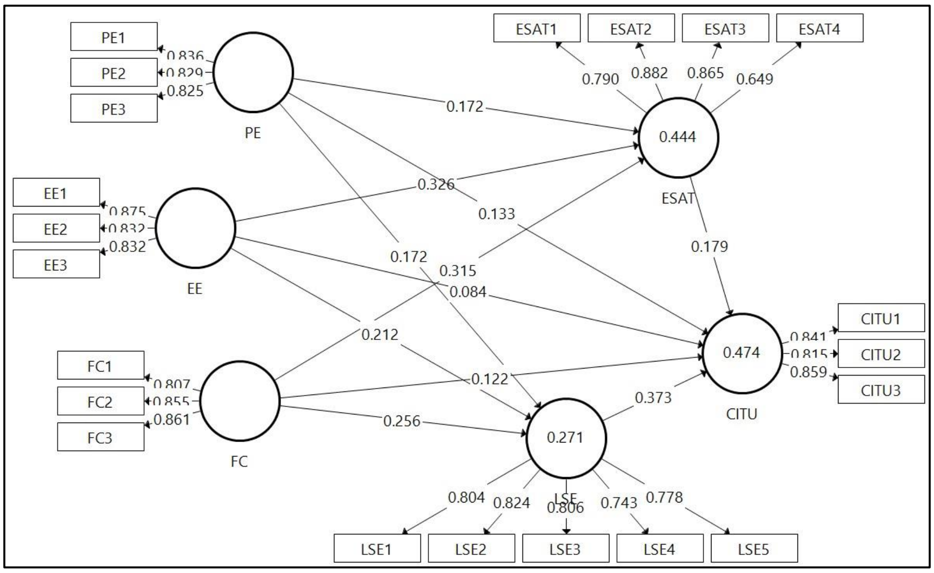

Figure 1: Research Framework
Notes: PE=Performance Expectancy EE=Effort Expectancy FC=Facilitating Conditions LSE=Learning Self-Efficacy ESAT=E-Satisfaction CITU=Continuous Intention to Use

Methodology
This study sought to assess the direct and indirect relationship between performance expectancy, effort expectancy, and facilitating conditions with the continuous intention to use the e-learning platform with the learning self-efficacy and e-satisfaction as the mediators among the students in open online flexible higher education institutions. To achieve this objective, researchers conducted a survey to collect primary data, meticulously examining previous research to select reliable and valid measurements. The survey questionnaires were then emailed to selected participants, utilizing purposive sampling due to the unavailability of a comprehensive population list. A total of 21 observed variables were scrutinized, including exogenous variables of effort expectancy (3 items), facilitating conditions (3 items), and performance expectancy (3 items) adopted from Venkatesh et al (2012), two mediators of e-satisfaction (4 items) adopted from Alalwan (2020) and learning self-efficacy (5 items) adopted from Kang et al (2019), while the dependent variable was continuous intention to use (3 items), adopted from (Dağhan & Akkoyunlu, 2016). A five-point Likert scale, ranging from strongly disagree to strongly agree, was utilized to assess components within each construct. Out of the 507 surveys distributed, 409 were returned, yielding an 80.7% response rate, deemed adequate for employing structural equation modeling (SEM) techniques in data analysis (Hair et al., 2019). Among the returned surveys, 377 were deemed clean and suitable for analysis. The choice of Smartpls4 software for data analysis and hypothesis testing was motivated by its robust assessment capabilities and proficiency in handling multivariate data analysis, aligning with the study's objectives and following the recommendations of (Ringle et al., 2022). Smartpls4 played a vital role in meticulously examining the proposed hypotheses and conducting extensive multivariate data analysis, facilitating a comprehensive evaluation of both measurement and structural models.

Data Analysis

Respondents Profile

The analysis reveals various demographic characteristics of the participants. Regarding gender, there were slightly more female respondents (51.2%, n=193) than male respondents (48.8%, n=184). In terms of age, the majority of participants were between 31 to 40 years old (45.1%, n=170), followed by those below 30 years old (39.5%, n=149). A smaller proportion fell into the 41 to 50 years age bracket (12.2%, n=46), with even fewer in the 51 to 60 years age range (3.2%, n=12). Concerning the year of study, the largest group consisted of third-year students (24.4%, n=92), followed closely by second-year students (21.2%, n=80) and fourth-year students (16.7%, n=63). Additionally, there were participants from the first year (18.8%, n=71), fifth year (11.4%, n=43), and beyond the fifth year (7.4%, n=28). In terms of the level of study, the majority were pursuing bachelor's degrees (65.8%, n=248), followed by diploma (21.5%, n=81), master's (8.0%, n=30), and doctorate (4.8%, n=18) degrees. Furthermore, an overwhelming majority of respondents (99.2%, n=374) indicated a positive recommendation to use e-learning platforms, while only a minimal percentage (0.8%, n=3) did not recommend its use. These findings provide valuable insights into the demographic composition and attitudes of the participants towards e-learning platforms, laying a foundation for further analysis and interpretation of the study results.

Common Method Bias

Kock (2015) and Kock & Lynn (2012) introduced a comprehensive technique known as the collinearity test, designed to tackle both vertical and horizontal collinearity concerns. Pathological collinearity is identified through variance inflation factors (VIFs) surpassing 3.3, signaling significant potential for common method bias within the model (Kock & Lynn, 2012). Thus, if the VIFs obtained from the thorough collinearity evaluation remain below 3.3, it can be inferred that the model remains unaffected by common method bias (Kock, 2015). As depicted in Table 1, the VIFs resulting from the overall collinearity assessment were observed to be under 3.3, affirming the absence of any common method bias issue within the model.

Table 1
Full Collinearity Test

	MCITU	MPE	MFC	MEE	MESAT	MLSE
MCITU		1.833	1.859	1.864	1.820	1.584
MPE	1.481		1.363	1.509	1.494	1.512
MFC	2.054	1.865		1.915	1.943	2.056
MEE	1.645	1.649	1.529		1.526	1.642
MESAT	1.818	1.847	1.756	1.727		1.872
MLSE	1.384	1.636	1.627	1.627	1.639	

Measurement Model

In this study, we employed the methodology advocated by Hair et al (2017) to evaluate each measurement in both the first and second orders, facilitating the identification of items with loadings below the 0.7 threshold. Analysis of construct reliability and validity revealed that the Average Variance Extracted (AVE) for all constructs ranged from 0.626 to 0.716, exceeding the 0.5 benchmark, thereby indicating robust convergent validity Hair et al (2017) (Table 2). Moreover, the composite reliability for all constructs surpassed 0.7, ranging from 0.869 to 0.893. Additionally, Cronbach's alpha coefficients for all constructs exceeded 0.7, ranging from 0.776 to 0.851 (Table 2). To ensure discriminant validity, the initial step involved assessing cross-loadings to ensure appropriate representation and measurement of respective constructs (Table 3). Subsequently, the Heterotrait-Monotrait (HTMT) ratio was utilized for further assessment, aligning with the recommended criterion for examining discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler, Ringle & Sarstedt, 2015). Table 4 presented the HTMT ratios alongside the original sample and 97.5% confidence intervals, confirming compliance with the HTMT threshold of 0.85.

Table 2
Construct Reliability & Validity

	CA	CR	AVE
CITU	0.789 (0.747, 0.831)	0.877 (0.855, 0.899)	0.703 (0.662, 0.747)
EE	0.802 (0.754, 0.842)	0.883 (0.858, 0.905)	0.716 (0.669, 0.761)
ESAT	0.809 (0.769, 0.848)	0.875 (0.853, 0.896)	0.643 (0.599, 0.690)
FC	0.794 (0.746, 0.833)	0.879 (0.851, 0.892)	0.707 (0.662, 0.749)
LSE	0.851 (0.818, 0.873)	0.893 (0.872, 0.908)	0.626 (0.578, 0.664)
PE	0.776 (0.714, 0.826)	0.869 (0.839, 0.897)	0.689 (0.633, 0.744)

Notes: 97.5% Confidence Interval Bootstrapping CA=Cronbach Alpha CR=Composite Reliability AVE=Average Variance Extracted

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	Ratios	2.50%	97.50%
EE -> CITU	0.550	0.444	0.648
ESAT -> CITU	0.644	0.528	0.746
ESAT -> EE	0.677	0.586	0.755
FC -> CITU	0.644	0.547	0.734
FC -> EE	0.682	0.595	0.783
FC -> ESAT	0.736	0.643	0.817
LSE -> CITU	0.716	0.634	0.789
LSE -> EE	0.488	0.380	0.588
LSE -> ESAT	0.517	0.391	0.627
LSE -> FC	0.556	0.442	0.654
PE -> CITU	0.569	0.438	0.682
PE -> EE	0.389	0.279	0.491
PE -> ESAT	0.556	0.433	0.658
PE -> FC	0.684	0.584	0.778
PE -> LSE	0.458	0.342	0.566

Notes: 97.5% Confidence Interval Bootstrapping

Table 4
Cross Loadings

	CITU	EE	ESAT	FC	LSE	PE
CITU1	**0.841**	0.444	0.444	0.491	0.538	0.406
CITU2	**0.815**	0.314	0.430	0.392	0.456	0.367
CITU3	**0.859**	0.350	0.424	0.421	0.487	0.350
EE1	0.404	**0.875**	0.538	0.541	0.360	0.279
EE2	0.386	**0.832**	0.442	0.420	0.355	0.289
EE3	0.333	**0.832**	0.418	0.437	0.316	0.223
ESAT1	0.353	0.391	**0.790**	0.438	0.290	0.335
ESAT2	0.407	0.488	**0.882**	0.518	0.312	0.358
ESAT3	0.488	0.528	**0.865**	0.503	0.380	0.419
ESAT4	0.395	0.346	**0.649**	0.425	0.387	0.311
FC1	0.355	0.378	0.468	**0.807**	0.321	0.417
FC2	0.412	0.493	0.520	**0.855**	0.367	0.393
FC3	0.529	0.513	0.501	**0.861**	0.474	0.561
LSE1	0.524	0.378	0.327	0.418	**0.804**	0.344
LSE2	0.470	0.326	0.353	0.396	**0.824**	0.307
LSE3	0.452	0.269	0.294	0.324	**0.806**	0.299
LSE4	0.446	0.297	0.313	0.335	**0.743**	0.267
LSE5	0.437	0.329	0.404	0.366	**0.778**	0.271
PE1	0.371	0.210	0.347	0.441	0.325	**0.836**
PE2	0.365	0.234	0.317	0.392	0.258	**0.829**
PE3	0.378	0.325	0.437	0.522	0.350	**0.825**

Structural Model

In this investigation, the assessment of the structural model adhered to the methodology delineated by Hair et al (2017), entailing the scrutiny of pathway coefficients (β) and coefficients of determination (R^2). The Partial Least Squares (PLS) method was employed, employing 5000 sub-samples to determine the significance level of path coefficients. The results from hypothesis testing, encompassing confidence intervals for path coefficients (beta), corresponding t-statistics, and p-values, are delineated in Table 5. This meticulous examination provides valuable insights into the significance and robustness of the relationships among the variables within the structural model. The comprehensive hypotheses testing outcomes in Table 5 furnish a nuanced analysis of each hypothesis, focusing on Beta coefficients, T-statistics, P-values, and the ultimate decisions regarding hypothesis support.

The hypotheses testing results indicate various significant relationships between the constructs. Starting with the relationship between effort expectancy and continuous intention to use (H1), the beta coefficient is 0.084 with a t-statistic of 1.670 and a p-value of 0.096, leading to the rejection of this hypothesis. However, effort expectancy demonstrates a significant positive influence on both e-satisfaction (H2) and learning self-efficacy (H3), with beta coefficients of 0.326 (t-statistic = 6.246, p-value = 0.000) and 0.212 (t-statistic = 3.860, p-value = 0.000), respectively, thus supporting H2 and H3. Furthermore, incorporating e-satisfaction and learning self-efficacy as mediators (H4 and H5) strengthens the relationship between effort expectancy and continuous intention to use, with significant beta coefficients of 0.058 (t-statistic = 2.816, p-value = 0.005) and 0.079 (t-statistic = 3.379, p-value = 0.001), respectively. Similarly, facilitating conditions exhibit significant positive effects on continuous intention to use (H6), e-satisfaction (H7), and learning self-efficacy (H8), with beta coefficients of 0.122 (t-statistic = 2.050, p-value = 0.041), 0.315 (t-statistic = 4.821, p-value = 0.000), and 0.256 (t-statistic = 4.047, p-value = 0.000), respectively, supporting H6, H7, and H8. Moreover, the inclusion of e-satisfaction and learning self-efficacy as mediators (H9 and H10) enhances the relationship between facilitating conditions and continuous intention to use, with significant beta coefficients of 0.056 (t-statistic = 2.482, p-value = 0.013) and 0.095 (t-statistic = 3.642, p-value = 0.000), respectively. Additionally, performance expectancy positively influences continuous intention to use (H11) and demonstrates significant effects on both e-satisfaction (H12) and learning self-efficacy (H13), with beta coefficients of 0.133 (t-statistic = 2.336, p-value = 0.020), 0.172 (t-statistic = 3.193, p-value = 0.001), and 0.172 (t-statistic = 3.295, p-value = 0.001), respectively, supporting H11, H12, and H13. Furthermore, e-satisfaction (H14) and learning self-efficacy (H15) significantly influence continuous intention to use, with beta coefficients of 0.179 (t-statistic = 2.977, p-value = 0.003) and 0.373 (t-statistic = 8.059, p-value = 0.000), respectively, supporting H14 and H15. Finally, incorporating e-satisfaction and learning self-efficacy as mediators (H16 and H17) strengthens the relationship between performance expectancy and continuous intention to use, with significant beta coefficients of 0.031 (t-statistic = 2.234, p-value = 0.026) and 0.064 (t-statistic = 2.892, p-value = 0.004), respectively, supporting H16 and H17. Overall, these findings provide comprehensive insights into the complex interplay among the constructs, confirming significant direct and mediated effects on continuous intention to use the e-learning platform among students in open online flexible higher education institutions.

Table 6 presents a comprehensive overview of effect sizes, evaluated independently of sample size, following Cohen's criteria (1992): small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes in the study ranged from small (0.008) to large (0.190). Intrinsic Value Inflation Factor (VIF) values, as detailed in Table 6, consistently remained below the more lenient threshold of 5, with the highest value recorded at 2.106. This level of collinearity facilitates meaningful comparisons of sizes and interpretation of coefficients within the structural model. A significant degree of explained variance for the endogenous construct is evident, with an R^2 value of 0.474 (Figure 1). Concerning the mediator, the model elucidated approximately 44.4% of the variance in the structure, as indicated by an R^2 value of 0.444.

The evaluation of the model's inference and managerial recommendations was conducted through out-of-sample predictive analysis employing the PLSpredict method (Shmueli et al., 2016, 2019). Table 7 illustrates that PLS-SEM generated superior Q^2 predictions (>0) compared to naive mean predictions, while consistently exhibiting lower RMSE values than linear model (LM) benchmarks, underscoring its predictive strength. Additionally, the RMSE values for PLS-SEM predictions consistently outperformed those of the linear model (LM) prediction benchmark in all nine instances, underscoring the predictive capability of the proposed model, as shown in Table 7. The introduction of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al (2022), and its integration with PLSpredict analysis by Liengaard et al. (2021), are noteworthy advancements. Table 8 reaffirms the superior predictive capabilities of PLS-SEM, with lower average loss values compared to indicator averages and LM benchmarks, providing further evidence of its enhanced predictive performance.

Ringle and Sarstedt (2016); Hair et al (2018) proposed Importance Performance Map Analysis (IPMA) to assess latent variable significance and effectiveness in explaining acceptance, as detailed in Table 8. The overall impact on continuous intention to use e-learning platform was most pronounced for learning self-efficacy (0.373), followed by facilitating conditions (0.273), performance expectancy (0.228), effort expectancy (0.222), and e-satisfaction (0.179), indicating their relative importance in continuous intention to use. Effort expectancy scored highest (69.276), while learning self-efficacy had the lowest score (60.603) on a 0-100 scale, reflecting better performance by effort expectancy and lower achievement for learning self-efficacy. Despite ranking first in continuous intention to use e-learning platform importance, the learning self-efficacy displayed the lowest performance. These results suggest prioritizing activities to improve learning self-efficacy among the students, potentially enhancing overall continuous intention to use the e-learning platform.

Table 5
Hypotheses Testing Results

Hypotheses	Beta	T-statistics	P-values	2.50%	97.50%	Decision
H1: EE -> CITU	0.084	1.670	0.096	-0.023	0.175	*Rejected*
H2: EE -> ESAT	0.326	6.246	0.000	0.228	0.426	*Accepted*
H3: EE -> LSE	0.212	3.860	0.000	0.092	0.309	*Accepted*
H4: EE -> ESAT -> CITU	0.058	2.816	0.005	0.020	0.102	*Accepted*
H5: EE -> LSE -> CITU	0.079	3.379	0.001	0.039	0.131	*Accepted*
H6: FC -> CITU	0.122	2.050	0.041	0.010	0.234	*Accepted*
H7: FC -> ESAT	0.315	4.821	0.000	0.184	0.434	*Accepted*
H8: FC -> LSE	0.256	4.047	0.000	0.146	0.388	*Accepted*
H9: FC -> ESAT -> CITU	0.056	2.482	0.013	0.022	0.112	*Accepted*
H10: FC -> LSE -> CITU	0.095	3.642	0.000	0.054	0.157	*Accepted*
H11: PE -> CITU	0.133	2.336	0.020	0.022	0.261	*Accepted*
H12: PE -> ESAT	0.172	3.193	0.001	0.066	0.274	*Accepted*
H13: PE -> LSE	0.172	3.295	0.001	0.062	0.264	*Accepted*
H14: ESAT -> CITU	0.179	2.977	0.003	0.053	0.287	*Accepted*
H15: LSE -> CITU	0.373	8.059	0.000	0.287	0.459	*Accepted*
H16: PE -> ESAT -> CITU	0.031	2.234	0.026	0.009	0.063	*Accepted*
H17: PE -> LSE -> CITU	0.064	2.892	0.004	0.022	0.108	*Accepted*

Table 6
Effect Sizes (f^2) & Variance Inflation Factor (VIF)

	f^2			VIF		
	CITU	ESAT	LSE	CITU	ESAT	LSE
EE	0.008	0.133	0.043	1.672	1.443	1.443
ESAT	0.033			1.828		
FC	0.013	0.096	0.048	2.106	1.866	1.866
LSE	0.190			1.394		
PE	0.022	0.037	0.028	1.517	1.434	1.434

Table 7
PLSpredicts

Indicators	PLS-RMSE	LM-RMSE	PLS-LM	Q^2_predict
CITU1	0.636	0.637	-0.001	0.292
CITU2	0.637	0.643	-0.006	0.186
CITU3	0.694	0.702	-0.008	0.202
ESAT1	0.725	0.736	-0.011	0.223
ESAT2	0.645	0.652	-0.007	0.320
ESAT3	0.625	0.626	-0.001	0.352
ESAT4	0.715	0.732	-0.017	0.194
LSE1	0.622	0.625	-0.003	0.210
LSE2	0.627	0.639	-0.012	0.170
LSE3	0.681	0.685	-0.004	0.119
LSE4	0.692	0.700	-0.008	0.128
LSE5	0.630	0.638	-0.008	0.150

Table 8
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-statistics	p-value
CITU	-0.129	5.428	0.000
ESAT	-0.171	5.884	0.000
LSE	-0.078	4.467	0.000
Overall	-0.122	6.828	0.000

Table 9
Importance-Performance Map Analysis (IPMA)

	Total Effect	Performance
EE	0.222	69.276
ESAT	0.179	63.712
FC	0.273	67.046
LSE	0.373	60.603
PE	0.228	66.860

Discussion

Effort expectancy, facilitating conditions, and performance expectancy are crucial determinants that can significantly influence students' continuous intention to use e-learning platforms in open online flexible higher education institutions. Based on the hypotheses testing findings, effective strategies can be devised to enhance these factors and positively impact students' engagement with e-learning platforms. Effort expectancy, representing the perceived ease of use of e-learning platforms, can be improved through various strategies. Providing user-friendly interfaces, intuitive navigation systems, and comprehensive tutorials can reduce perceived complexity and enhance students' confidence to utilize the platform effectively. Additionally, offering technical support services and troubleshooting guides can address any potential challenges students may encounter, further enhancing their perception of effort expectancy. Facilitating conditions encompass the availability of resources, support, and technical infrastructure necessary for effective e-learning. Institutions can invest in robust IT infrastructure to enhance facilitating conditions, ensuring reliable internet connectivity and access to necessary software and tools. Moreover, providing training and support services for students and instructors can empower them to maximize the potential of e-learning platforms. Creating a supportive learning environment, both virtually and physically, where students can collaborate, communicate, and access resources seamlessly, can further strengthen facilitating conditions and encourage continuous engagement with the e-learning platform. Performance expectancy reflects students' perceptions of the benefits and usefulness of e-learning platforms. To enhance performance expectancy, institutions can focus on demonstrating the value and relevance of the platform in supporting students' academic goals and enhancing their learning experiences. Incorporating interactive and multimedia-rich content, personalized learning pathways, and real-world applications can enhance the perceived usefulness of the platform. Additionally, showcasing success stories and testimonials from peers who have benefited from the platform can further reinforce students' confidence in its effectiveness. By implementing these effective strategies to enhance effort expectancy, facilitating conditions, and performance expectancy, higher education institutions can foster a conducive environment for e-learning adoption and promote continuous intention to use the platform among students in open online flexible settings.

Theoretical Implications

The study findings carry significant theoretical implications, particularly in relation to the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT posits that performance expectancy, effort expectancy, facilitating conditions, and social influence collectively influence users' behavioral intentions and actual technology usage. The study's findings corroborate several key tenets of UTAUT, affirming the theory's relevance in understanding students' continuous intention to use e-learning platforms in open online flexible higher education institutions. Firstly, the positive relationships observed between effort expectancy, facilitating conditions, performance expectancy, and continuous intention to use the e-learning platform align with UTAUT's propositions. Effort expectancy, reflecting the perceived ease of use, positively influences users' intention to continue using the platform, consistent with UTAUT's emphasis on usability as a determinant of technology acceptance. Similarly, facilitating conditions, encompassing the availability of resources and support, positively impact users' intention to use the platform, as predicted by UTAUT. Furthermore, the study's findings regarding the mediating roles of e-satisfaction and learning self-efficacy provide insights into the underlying mechanisms through which UTAUT's determinants influence behavioral intentions. E-satisfaction, stemming from users' satisfaction with the e-learning experience, and learning self-efficacy, reflecting users' confidence in their ability to succeed in learning tasks, mediate the relationships between effort expectancy, facilitating conditions, performance expectancy, and continuous intention to use the platform. These mediating effects underscore the importance of users' subjective experiences and perceptions in shaping their intentions and actual usage behavior, as emphasized by UTAUT.

Practical Implications

The study findings yield several practical implications for open online flexible higher education institutions seeking to enhance students' engagement with e-learning platforms. Firstly, institutions can focus on optimizing the usability of e-learning platforms by prioritizing user-friendly interfaces, intuitive navigation, and comprehensive support resources. Providing technical assistance and tutorials can help students overcome potential barriers and enhance their confidence in using the platform effectively. Moreover, investing in robust IT infrastructure and ensuring reliable internet connectivity can mitigate technical challenges and ensure a seamless learning experience for students. Additionally, institutions can enhance facilitating conditions by providing comprehensive support services, including training for both students and instructors, access to necessary software and tools, and creating a supportive virtual learning environment. Encouraging collaboration, communication, and resource-sharing among students can further enrich the learning experience and foster a sense of community within the online learning environment. Furthermore, highlighting the benefits and relevance of e-learning platforms in supporting students' academic goals and enhancing their learning experiences can strengthen students' motivation and willingness to engage with the platform continuously. Sharing success stories and testimonials from peers can also inspire confidence and demonstrate the practical value of e-learning. Overall, by implementing these practical strategies, open online flexible higher education institutions can effectively promote student engagement and maximize the potential of e-learning platforms for enhanced learning outcomes.

Suggestion for Future Study
Future studies could further explore the role of additional factors that may influence students' continuous intention to use e-learning platforms in open online flexible higher education institutions. For instance, investigating the impact of individual differences such as learning styles, personality traits, and technological literacy on users' perceptions and behaviors could provide valuable insights. Additionally, longitudinal studies could be conducted to examine the long-term effects of e-learning platform usage on students' academic performance and satisfaction. Furthermore, exploring the effectiveness of different interventions and strategies aimed at enhancing users' experience and engagement with e-learning platforms could offer practical recommendations for institutions seeking to optimize their online learning environments. Lastly, comparative studies across different institutional contexts and student demographics could help identify unique challenges and opportunities for e-learning adoption and usage, contributing to a more comprehensive understanding of technology acceptance and usage behavior in higher education.

Conclusion
The study provides valuable insights into the factors influencing students' continuous intention to use e-learning platforms in open online flexible higher education institutions. Effort expectancy, facilitating conditions, and performance expectancy emerged as significant determinants of students' intention to engage with e-learning platforms continuously. Additionally, e-satisfaction and learning self-efficacy were identified as important mediators in the relationship between these determinants and continuous intention to use. The findings underscore the importance of providing user-friendly interfaces, and comprehensive support services and demonstrating the practical benefits of e-learning platforms in fostering students' engagement and satisfaction. Moreover, the study highlights the relevance of theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) in understanding technology acceptance and usage behavior in the context of higher education. Overall, the study contributes to a better understanding of the dynamics of e-learning adoption and usage among students, offering practical implications for institutions seeking to enhance their online learning environments.

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