

LMS Acceptance Factors and Students' Digital Learning Practices: The Mediating Role of Learning Experience

Fenny Damayanti ^(1*) Chandra Hendriyani ⁽²⁾ Tengku Sitti Rochmah ⁽³⁾
Nadia Rizky Vindiazhari ⁽⁴⁾

^(1,4) Department of Management, Universitas Taruna Bakti, Bandung, Indonesia

^(2,3) Department of Secretary, Universitas Taruna Bakti, Bandung, Indonesia

Received: 2026, 06, 29 Accepted: 2026, 10, 12

Available online: 2026, 10, 28

* Corresponding author.

E-mail addresses: fenny.damayanti@tbu.ac.id

KEYWORDS	ABSTRACT
Keywords: Digital Engagement; Digital Integration in Daily Life; Learning Experience; Learning Management System; UTAUT2. Conflict of Interest Statement: The author(s) declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. Copyright © 2026 Vifada Management and Social Sciences. All rights reserved.	Purpose: This research investigates whether Performance Expectancy, Effort Expectancy, and Facilitating Conditions are associated with Learning Experience and whether they have indirect associations with Digital Engagement and Digital Integration in Daily Life through that experience. Research Method: Survey responses from 114 university students who had used an LMS were examined with Partial Least Squares Structural Equation Modeling (PLS-SEM). Results and Discussion: Students reported better Learning Experience when they perceived stronger performance benefits and more adequate Facilitating Conditions. Effort Expectancy was not significantly associated with Learning Experience. Learning Experience, in turn, was positively related to Digital Engagement and Digital Integration in Daily Life. The indirect associations originating from Performance Expectancy and Facilitating Conditions were significant, whereas those originating from Effort Expectancy were not. Because Learning Experience and Digital Engagement showed only marginal empirical separation, findings involving these constructs require caution. The model did not include direct links from the acceptance factors to either outcome; consequently, the form of mediation cannot be determined. Implications: Universities can improve LMS-based learning by strengthening its educational value, ensuring access to support, and designing activities that students regard as meaningful. Future studies should use stronger measurement checks and longitudinal evidence. Originality: The study uses selected UTAUT2 constructs to investigate Learning Experience as an experiential bridge between students' perceptions of an LMS and their subsequent digital learning practices.

1) Introduction

Higher education institutions increasingly regard digital transformation as essential to educational quality, organizational performance, and competitiveness. This transformation is not limited to acquiring technology; it also requires universities to redesign academic processes, use resources more effectively, and incorporate digital information into managerial decisions ([Verhoef et al., 2021](#); [Vial, 2019](#)). Consequently, technology implementation must be managed as an institutional change rather than solely as a teaching initiative ([Abdelfattah et al., 2024](#); [Mella-Norambuena et al., 2025](#)).

Learning Management Systems (LMSs) illustrate this institutional change. Their role has expanded beyond storing course materials to supporting delivery, interaction, assessment, feedback, and learning analytics. At the same time, these platforms create records of learning and teaching activities ([Drugova et al., 2024](#); [Paulsen & Lindsay, 2024](#)). Such functions may improve students' experiences and provide information for monitoring academic progress, assuring quality, and making institutional decisions ([Long & Siemens, 2011](#)).

Much of the LMS literature nevertheless explains adoption rather than what follows sustained use. Studies based on technology acceptance models commonly examine usefulness, ease of use, intention, and usage ([Granić & Marangunić, 2019](#)). Reviews of UTAUT research reach a similar conclusion: acceptance remains the dominant endpoint, while subsequent educational and organizational consequences receive less attention ([Xue et al., 2024](#); [Zheng et al., 2025](#)). Other LMS studies emphasize satisfaction, system quality, support conditions, and adoption determinants

([Abdelfattah et al., 2024](#); [Alkhateeb & Abdalla, 2021](#); [Al-Samarraie et al., 2017](#)). These streams explain why students use an LMS more clearly than the value that emerges after adoption.

An unresolved question is how continued LMS use becomes part of students' digital learning practices. Regular interaction with the platform may foster participation, self-regulation, collaboration, and the incorporation of technology into daily academic routines ([Ng, 2012](#); [van Laar et al., 2019](#)). These practices may strengthen students' digital readiness and universities' capacity for continuing educational innovation. Yet adoption is frequently treated as the final outcome, leaving the experiential process between system perceptions and sustained digital practices insufficiently explained.

This issue also points to a boundary of UTAUT2. The framework explains technology acceptance effectively ([Venkatesh et al., 2012](#)), but it says less about the experience through which acceptance-related perceptions may be translated into post-adoption practices. We therefore position Learning Experience as that experiential link. It captures students' cognitive, emotional, behavioral, and social evaluations of learning in a digital environment ([Jahnke et al., 2022](#)). Through a meaningful experience, perceptions of usefulness, usability, and institutional support may be reflected in stronger Digital Engagement and greater integration of the LMS into academic routines. LMS records may additionally inform transparency, accountability, and evidence-based academic management ([Long & Siemens, 2011](#); [Wahyudin et al., 2017](#)), although governance itself is not measured in this study.

Accordingly, the analysis tests how Performance Expectancy, Effort Expectancy, and Facilitating Conditions relate to Learning Experience, and how Learning Experience relates to Digital Engagement and Digital Integration in Daily Life. It also estimates the specific indirect associations of the three acceptance factors with both outcomes through Learning Experience. By using selected UTAUT2 constructs in an existing-user context, the study shifts attention from initial acceptance to the experiences and practices that follow LMS use. Its proposed contribution is an experiential account of how acceptance-related perceptions connect with active participation and routine academic use.

2) Literature Review and Hypothesis Development

Acceptance Factors and Learning Experience

UTAUT2 identifies several perceptions and conditions that shape technology acceptance and use ([Venkatesh et al., 2012](#)). This study focuses on Performance Expectancy, Effort Expectancy, and Facilitating Conditions because they respectively represent the learning value students expect from an LMS, the effort required to use it, and the support available for its use. Rather than assessing the complete UTAUT2 framework or students' initial adoption decisions, the study examines how these three factors relate to the experiences of students who already use an LMS.

Performance Expectancy captures the extent to which students believe that an LMS helps them learn and perform academic tasks. Effort Expectancy represents how easily students can understand, navigate, and operate the platform. Facilitating Conditions concern the resources that enable its use, including suitable devices, internet connectivity, and technical assistance. Although these constructs address different aspects of LMS use, each may contribute to how students subsequently evaluate their learning experience.

In this study, Learning Experience denotes students' appraisal of the learning they undertake through an LMS. This concept differs from Learning Experience Design (LXD), which concerns the intentional design of learning activities and environments to facilitate worthwhile learner experiences. The perspective offered by [Jahnke et al. \(2022\)](#) helps explain how a designed environment may shape what learners experience. However, the present study measures students' perceived experience rather than the implementation or quality of the design process.

The expected relationships follow from these conceptual distinctions. When an LMS helps students complete academic work, they may evaluate the resulting learning experience more favorably. An easily operated platform may reduce the attention required to overcome technical difficulties, while reliable resources and assistance may prevent disruptions during learning. Evidence from Moodle users similarly connects students' evaluations of the platform with perceived usefulness and usability ([Alkhateeb & Abdalla, 2021](#)). The present study therefore examines whether the three acceptance-related factors explain differences in Learning Experience among existing LMS users. Accordingly, the following hypotheses are proposed:

H1: Performance Expectancy positively influences Learning Experience.

H2: Effort Expectancy positively influences Learning Experience.

H3: Facilitating Conditions positively influence Learning Experience.

Learning Experience and Digital Learning Practices

As students use digital technologies repeatedly, these technologies may gradually influence how they obtain information, communicate, and organize their academic work. However, participation in technology-enabled learning should not automatically be interpreted as evidence of a comprehensive digital culture or digital competence. [Ng \(2012\)](#) distinguishes familiarity with technology from the ability to use it effectively for learning. This study therefore concentrates on two more specific practices: Digital Engagement and Digital Integration in Daily Life.

Digital Engagement captures students' active participation in LMS-enabled learning, including online discussions, interactive assignments, and collaborative activities. It concerns what students do during the learning process. Learning Experience, by contrast, reflects how students evaluate the learning they undergo. Students may therefore participate frequently in digital activities without necessarily regarding the resulting experience as meaningful or satisfactory.

Digital Integration in Daily Life indicates that LMS use has become part of students' ordinary academic routines, such as consulting course information, reading announcements, and organizing assignments. The construct is limited to academic activities and does not represent the use of technology in every aspect of life. It also differs from Digital Engagement: students may access an LMS routinely without participating intensively in interactive activities, while engagement in particular activities does not necessarily mean that LMS use has become habitual.

Learning Experience may help explain both digital learning practices. When students consider LMS-supported learning useful and meaningful, they may become more inclined to participate in subsequent activities and incorporate the platform into their regular study routines. LXD scholarship supports this reasoning by drawing attention to the relationship between a learning environment and the experience it produces ([Jahnke et al., 2022](#)). Building on this perspective, the study tests whether a favorable Learning Experience is associated with active digital participation and routine academic use.

These relationships are proposed as theoretically plausible associations. The cross-sectional design does not establish whether positive learning experiences precede the development of these practices, and reciprocal relationships remain possible. Accordingly, the following hypotheses are proposed:

H4: Learning Experience positively influences Digital Engagement.

H5: Learning Experience positively influences Digital Integration in Daily Life.

The Mediating Role of Learning Experience

Acceptance-related factors explain what students think about the educational value, usability, and supporting resources of an LMS. However, these perceptions do not directly indicate whether students regard the learning conducted through the platform as meaningful. Learning Experience is therefore examined as an experiential link between students' perceptions of the LMS and their subsequent Digital Engagement and Digital Integration in Daily Life.

The proposed process begins with the conditions students perceive when using an LMS. Performance Expectancy may contribute to Learning Experience when the platform helps students complete academic work more effectively. Effort Expectancy may become relevant when ease of operation allows students to focus on learning rather than navigating the system. Facilitating Conditions may improve the experience by ensuring that students have adequate resources and assistance. This reasoning combines the acceptance constructs described by [Venkatesh et al. \(2012\)](#) with the learner-oriented perspective discussed by [Jahnke et al. \(2022\)](#).

A favorable Learning Experience may subsequently encourage students to participate in LMS-supported activities and make platform use part of their academic routines. It thus represents one possible route through which perceived benefits, usability, and available support are connected with digital learning practices. By examining this route, the study moves beyond acceptance itself and considers the experiential process that may accompany students' post-adoption behavior.

Learning Experience is proposed as an experiential pathway connecting LMS acceptance factors with digital learning practices. The present analysis examines specific indirect effects through Learning Experience within the specified model. Direct paths from the three acceptance factors to Digital Engagement and Digital Integration in Daily Life were not estimated. Accordingly, the analysis does not determine whether the indirect relationships coexist with direct effects and does not distinguish full, partial, or indirect-only mediation. The cross-sectional design also prevents the establishment of a temporal or causal sequence. Accordingly, the following hypotheses are proposed:

H6: Performance Expectancy has a positive indirect effect on Digital Engagement through Learning Experience.

H7: Performance Expectancy has a positive indirect effect on Digital Integration in Daily Life through Learning Experience.

- H8:** Effort Expectancy has a positive indirect effect on Digital Engagement through Learning Experience.
H9: Effort Expectancy has a positive indirect effect on Digital Integration in Daily Life through Learning Experience.
H10: Facilitating Conditions have a positive indirect effect on Digital Engagement through Learning Experience.
H11: Facilitating Conditions have a positive indirect effect on Digital Integration in Daily Life through Learning Experience.

Conceptual Framework

The proposed model explains students' digital learning practices after LMS adoption by placing Learning Experience between selected acceptance factors and the two outcomes. It incorporates Performance Expectancy, Effort Expectancy, and Facilitating Conditions from UTAUT2 without claiming to test the framework in its entirety (Venkatesh et al., 2012). Within the model, Learning Experience represents the proposed experiential mechanism, while Digital Engagement and Digital Integration in Daily Life capture two different practices associated with continued LMS use.

Each group of constructs occupies a different position in the model. Performance Expectancy, Effort Expectancy, and Facilitating Conditions represent students' assessments of the LMS's benefits, ease of use, and supporting resources. Learning Experience captures how students evaluate learning through the platform. Digital Engagement reflects active participation in technology-enabled learning, whereas Digital Integration in Daily Life reflects the incorporation of LMS use into regular academic routines.

H1-H3 propose positive relationships between the three LMS acceptance factors and Learning Experience. H4 and H5 propose positive relationships between Learning Experience and the two digital learning outcomes. H6-H11 examine the specific indirect effects of each acceptance factor on each outcome through Learning Experience.

The framework concerns associations among individual students' perceptions, experiences, and practices. It does not directly measure institutional digital transformation, digital competence, or Good University Governance. These broader issues may inform the discussion of practical implications but are outside the empirical scope of the model. Figure 1 presents the five direct relationships specified in H1-H5. H6-H11 represent the specific indirect relationships through Learning Experience.

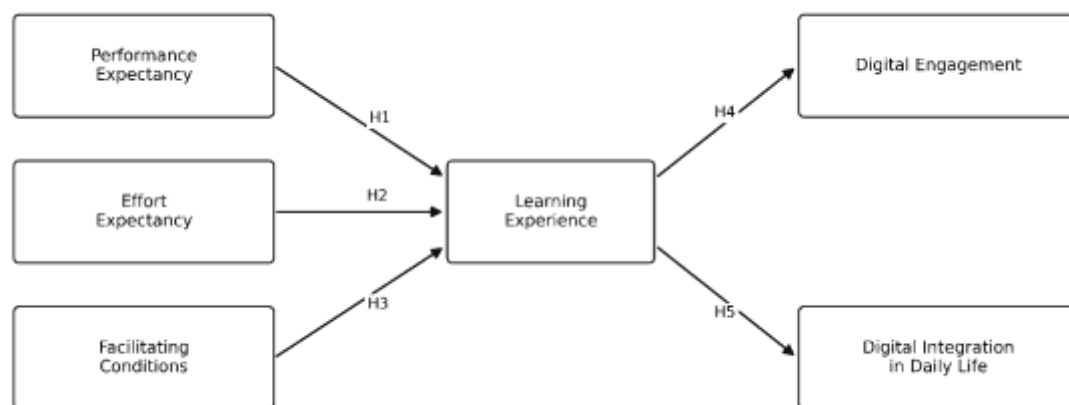


Figure 1. Proposed Conceptual Framework

Note. Arrows represent the direct relationships specified in H1-H5. H6-H11 concern specific indirect effects through Learning Experience and are not represented by separate arrows.

3) Research Design and Methodology

Research Design

A quantitative cross-sectional survey was used to investigate the associations among LMS acceptance factors, Learning Experience, and students' digital learning practices. Information was collected once from students who had previously used an LMS. The study therefore addresses perceptions and practices occurring after adoption rather than students' decisions to begin using the platform.

The proposed model was estimated with Partial Least Squares Structural Equation Modeling (PLS-SEM). This method enabled the measurement relationships and the specified direct and indirect associations to be examined within a single model (Hair & Alamer, 2022). Learning Experience was

specified as the proposed intervening construct between Performance Expectancy, Effort Expectancy, and Facilitating Conditions and the two digital learning outcomes.

The relationships are theoretically directional, but observations collected at one point in time cannot establish their temporal order or demonstrate causation. Accordingly, the estimated paths and indirect effects are interpreted as associations that are compatible with the proposed framework. Alternative processes remain possible, including the possibility that students' engagement influences how they evaluate their learning experiences.

Population, Sample, and Sampling Technique

The study focused on active university students who had used an LMS for academic purposes. Because a complete list of eligible students was unavailable, respondents were selected purposively. Participation required active undergraduate or postgraduate status, experience using an LMS in at least three courses, and voluntary consent. These requirements were established to ensure that respondents could evaluate LMS-supported learning on the basis of their own experience.

The initial sample requirement was determined through an a priori power calculation in G*Power ([Faul et al., 2009](#)). The calculation specified a medium effect size of $f^2 = 0.15$, $\alpha = 0.05$, statistical power of 0.80, and three predictors of Learning Experience, resulting in a minimum requirement of 77 respondents. After incomplete or invalid submissions had been screened out, 114 responses were retained for analysis.

Because purposive sampling was used, the sample should not be considered statistically representative of the broader university student population. The findings are interpreted within the characteristics and LMS-use context of the participating students.

Research Instrument

The instrument contained 23 statements covering six constructs: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Learning Experience, Digital Engagement, and Digital Integration in Daily Life. Facilitating Conditions was represented by three statements, while four statements were used for each of the other constructs. Responses were recorded on a five-point scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

The measures of Performance Expectancy, Effort Expectancy, and Facilitating Conditions were contextualized for students' use of an LMS and informed by the acceptance constructs developed by [Venkatesh et al. \(2012\)](#). The three measures respectively captured the learning benefits students expected from the platform, the effort involved in operating it, and the resources available to support its use.

Learning Experience measured students' appraisal of learning conducted through the LMS. The LXD literature was used to clarify the conceptual meaning of learner experience ([Jahnke et al., 2022](#)), but it was not treated as a previously validated measurement scale for this construct. Digital Engagement captured active participation in LMS-supported activities, while Digital Integration in Daily Life captured the incorporation of platform use into regular academic routines. These constructs represent specific learning practices rather than digital culture in its entirety.

Before the main data collection, 30 university students completed a pilot version of the questionnaire. The pilot was used to examine whether the items were understandable and showed adequate preliminary consistency, with Cronbach's alpha of 0.70 used as the minimum reference. In the main sample, convergent validity was evaluated from indicator loadings and AVE, while Cronbach's alpha and composite reliability were used to assess internal consistency. The Fornell-Larcker criterion was applied separately to evaluate discriminant validity, particularly because Learning Experience and Digital Engagement were closely related.

Data Analysis Technique

SmartPLS was used to estimate the PLS-SEM model. The analysis first evaluated the relationships between each construct and its indicators and then examined the structural relationships among the constructs. The latter included the specific indirect associations proposed through Learning Experience ([Hair & Alamer, 2022](#)).

For the measurement model, indicator loadings and AVE were used to assess convergent validity, whereas Cronbach's alpha and composite reliability were used to assess internal consistency. Loadings near or above 0.70, reliability coefficients above 0.70, and AVE above 0.50 were treated as satisfactory. Construct separation was examined using the Fornell-Larcker criterion by comparing the square root of each construct's AVE with its correlations with the other constructs. Because this criterion may not always detect insufficient separation, marginal results were interpreted cautiously. HTMT was not available in the reported analysis.

Indicator VIF values were compared with the reference value of 5.00 to identify excessive collinearity at the measurement level. This assessment was not interpreted as evidence concerning collinearity among predictors in the structural model.

The structural assessment used R^2 and adjusted R^2 to describe the variance accounted for in each endogenous construct. The reported Q^2 statistic was used to examine predictive relevance under the procedure originally applied. Positive Q^2 values were not interpreted as evidence that the model would necessarily predict observations outside the analyzed sample. SRMR and NFI were considered supplementary diagnostics rather than decisive tests of model adequacy.

The hypotheses were assessed from the bootstrapped standardized coefficients, t-statistics, and p-values. A directional hypothesis was supported when the estimated coefficient was positive and its p-value was below 0.05. The specific indirect associations were examined from each acceptance factor to Digital Engagement and Digital Integration in Daily Life through Learning Experience.

The model did not estimate direct paths from the three LMS acceptance factors to the two digital learning outcomes. Consequently, significant specific indirect effects were interpreted as evidence consistent with the proposed experiential pathway within the specified model, without classifying mediation as full, partial, or indirect-only. All structural relationships were interpreted within the limitations of the cross-sectional design.

4) Results and Discussion

a) Results

The results are organized into three parts: respondent characteristics, measurement quality, and structural relationships. Evidence concerning the measurement model is presented before the hypothesized relationships are evaluated.

Table 1. Demographic Characteristics of Respondents

Characteristics	Category	Frequency (n)	Percentage (%)
Gender	Female	107	93.86
	Male	7	6.14
	Total	114	100.00
Academic Semester	Semester 1	2	1.75
	Semester 2	12	10.53
	Semester 3	11	9.65
	Semester 4	20	17.54
	Semester 5	12	10.53
	Semester 6	48	42.11
	Semester 7	2	1.75
	Semester 8	7	6.14
	Total	114	100.00

A total of 114 valid responses were analyzed. As presented in Table 1, 107 respondents were female (93.86%) and seven were male (6.14%). The sample therefore predominantly reflects the perceptions and digital learning practices of female participants. This imbalance limits the generalizability of the findings to student populations with different gender compositions and does not provide a sufficient basis for meaningful comparisons between male and female respondents.

Regarding academic semester, the largest group comprised students in Semester 6 (42.11%, $n = 48$), followed by Semester 4 (17.54%, $n = 20$). Semesters 2 and 5 each accounted for 10.53% ($n = 12$), while Semester 3 represented 9.65% ($n = 11$). Students in Semester 8 accounted for 6.14% ($n = 7$), and Semesters 1 and 7 each represented 1.75% ($n = 2$).

These characteristics describe the composition of the participating sample rather than the broader university student population. Although Semester 6 students formed the largest group, academic semester alone does not establish the duration or intensity of LMS use. Respondents' eligibility to evaluate LMS-supported learning was based on the LMS-use criteria specified in the sampling procedure.

Table 2. Measurement Model Assessment: Reliability and Convergent Validity

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
Digital Engagement (DE)	DE1	0.737	0.866	0.909	0.714
	DE2	0.866			
	DE3	0.892			
	DE4	0.876			
Digital Integration in Daily Life (DI)	DI1	0.883	0.892	0.925	0.755
	DI2	0.867			
	DI3	0.854			
	DI4	0.871			
Effort Expectancy (EE)	EE1	0.869	0.896	0.928	0.762
	EE2	0.878			
	EE3	0.891			
	EE4	0.854			
Facilitating Conditions (FC)	FC1	0.848	0.777	0.870	0.691
	FC2	0.821			
	FC3	0.824			
Learning Experience (LE)	LE1	0.887	0.908	0.936	0.784
	LE2	0.870			
	LE3	0.877			
	LE4	0.907			
Performance Expectancy (PE)	PE1	0.871	0.898	0.929	0.766
	PE2	0.890			
	PE3	0.852			
	PE4	0.888			

Table 2 summarizes the quality of the reflective measures. Indicator loadings fall between 0.737 and 0.907, with every value exceeding the approximate reference of 0.70. Thus, each indicator shows an adequate association with the construct to which it was assigned.

Cronbach's alpha ranges from 0.777 to 0.908, while composite reliability ranges from 0.870 to 0.936. Both sets of coefficients are above 0.70 and therefore indicate adequate internal consistency. AVE ranges between 0.691 and 0.784, showing that each construct accounts for more than half of the variance in its indicators on average ([Hair & Alamer, 2022](#)).

These findings provide evidence of internal consistency and convergent validity. They do not, however, demonstrate that the six constructs are empirically distinct. Construct separation is considered separately in Table 4, with particular attention given to Learning Experience and Digital Engagement.

Table 3. Collinearity Assessment of the Measurement Model

Construct	Indicator	VIF
Digital Engagement (DE)	DE1	1.640
	DE2	2.456
	DE3	2.800
	DE4	2.466
Digital Integration in Daily Life (DI)	DI1	2.888
	DI2	2.765
	DI3	2.487
	DI4	2.627
Effort Expectancy (EE)	EE1	2.292
	EE2	2.750

Construct	Indicator	VIF
Facilitating Conditions (FC)	EE3	2.782
	EE4	2.379
	FC1	1.799
	FC2	1.662
	FC3	1.470
Learning Experience (LE)	LE1	2.914
	LE2	2.662
	LE3	3.014
	LE4	3.523
Performance Expectancy (PE)	PE1	2.440
	PE2	2.789
	PE3	2.218
	PE4	2.681

The indicator VIF values reported in Table 3 range from 1.470 to 3.523 and remain below 5.00. Under this reference, no indicator displays excessive collinearity. LE4 records the highest value, whereas FC3 records the lowest.

These results concern collinearity among measurement indicators and should be distinguished from collinearity among predictors in the structural model. They do not establish whether Performance Expectancy, Effort Expectancy, and Facilitating Conditions exhibit excessive collinearity when jointly predicting Learning Experience. Structural predictor VIF values were not included in the reported analysis. Accordingly, Table 3 is interpreted as an indicator-level diagnostic rather than evidence that collinearity is absent throughout the model.

Table 4. The Discriminant Validity Assessment Using the Fornell-Larcker Criterion

Construct	DE	DI	EE	FC	LE	PE
Digital Engagement (DE)	0.846					
Digital Integration in Daily Life (DI)	0.784	0.869				
Effort Expectancy (EE)	0.686	0.779	0.873			
Facilitating Conditions (FC)	0.599	0.690	0.793	0.831		
Learning Experience (LE)	0.845	0.793	0.745	0.756	0.885	
Performance Expectancy (PE)	0.669	0.801	0.803	0.753	0.810	0.875

Table 4 evaluates discriminant validity using the Fornell-Larcker criterion. At the level of numerical precision reported in the table, the square root of AVE for every construct is larger than its correlations with the remaining constructs. The model therefore satisfies this criterion formally.

However, the square root of AVE for Digital Engagement (0.846) exceeds its correlation with Learning Experience (0.845) by only 0.001. This marginal difference warrants caution and does not provide strong evidence of empirical separation between the two constructs. Conceptually, Learning Experience concerns students' evaluation of their LMS-supported learning experiences, whereas Digital Engagement concerns their active participation in digital learning activities. This conceptual distinction does not, by itself, resolve the limited empirical separation observed in Table 4.

HTMT results were not available in the reported analysis. Accordingly, discriminant validity should be regarded as provisionally supported by the Fornell-Larcker criterion rather than conclusively established. The relationship between Learning Experience and Digital Engagement, together with the indirect effects leading to Digital Engagement, should be interpreted with this measurement limitation in mind.

Table 5. Model Fit Assessment

Model Fit Index	Saturated Model	Estimated Model
SRMR	0.073	0.089
d_ULS	1.467	2.196
d_G	0.963	1.114

Model Fit Index	Saturated Model	Estimated Model
Chi-square	584.443	632.421
NFI	0.773	0.754

Table 5 provides supplementary information about model fit. SRMR equals 0.073 for the saturated model and 0.089 for the estimated model. The latter exceeds the conservative reference of 0.08 but remains below the more permissive value of 0.10 (SmartPLS, n.d.). It should therefore not be presented as unambiguous evidence that the model fits the data well.

The NFI values are 0.773 for the saturated model and 0.754 for the estimated model. These relatively low values provide limited support for overall model fit. Accordingly, the SRMR result should not be used in isolation to conclude that the proposed model adequately reproduces the observed relationships.

The reported d_ULS values are 1.467 and 2.196, while d_G values are 0.963 and 1.114 for the saturated and estimated models, respectively. Bootstrap reference values for these discrepancy measures were not available, preventing a formal assessment of exact fit. The chi-square values are reported descriptively and are not used independently to establish model adequacy.

Taken together, these diagnostics provide mixed evidence regarding model fit. The estimated model is therefore interpreted with reference to its measurement properties and structural results, while acknowledging the relatively low NFI and the marginal empirical distinction between Learning Experience and Digital Engagement. Significant structural paths do not, by themselves, resolve these limitations.

Table 6. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Construct	R^2	Adjusted R^2	Q^2
Digital Engagement	0.716	0.714	0.498
Digital Integration in Daily Life	0.629	0.626	0.468
Learning Experience	0.708	0.700	0.537

Table 6 reports the variance accounted for in the three endogenous constructs. Performance Expectancy, Effort Expectancy, and Facilitating Conditions jointly account for 70.8% of the variance in Learning Experience ($R^2 = 0.708$; adjusted $R^2 = 0.700$). Within the specified model, Learning Experience accounts for 71.6% of the variance in Digital Engagement ($R^2 = 0.716$; adjusted $R^2 = 0.714$) and 62.9% of the variance in Digital Integration in Daily Life ($R^2 = 0.629$; adjusted $R^2 = 0.626$).

These values indicate substantial explanatory capacity within the analyzed sample. However, explained variance does not establish causality or overall model validity. In particular, the R^2 for Digital Engagement should be interpreted alongside the limited empirical separation between Digital Engagement and Learning Experience identified in Table 4. Their close association may partly reflect overlap in measurement rather than exclusively distinct explanatory relationships.

The reported Q^2 values are positive for Learning Experience (0.537), Digital Engagement (0.498), and Digital Integration in Daily Life (0.468). These results suggest predictive relevance under the procedure used to calculate them. Since the calculation settings and an independent assessment of predictive performance were not available, the values are not interpreted as evidence that the model accurately predicts outcomes for new students or other institutional contexts.

Overall, Table 6 supports the model's explanatory capacity within the sample, while the measurement limitations, model fit diagnostics, and cross-sectional design constrain broader interpretations of its explanatory and predictive performance.

Table 7. Hypothesis Testing Results

Hypothesis Path	β	t-value	P-value	Decision
H1 Performance Expectancy → Learning Experience	0.502	5.697	<0.001	Supported
H2 Effort Expectancy → Learning Experience	0.114	0.951	0.342	Not supported
H3 Facilitating Conditions → Learning Experience	0.288	3.216	0.001	Supported
H4 Learning Experience → Digital Engagement	0.846	28.128	<0.001	Supported
H5 Learning Experience → Digital Integration in Daily Life	0.793	15.581	<0.001	Supported

Note. B = standardized path coefficient. A hypothesis is considered supported when $p < 0.05$.

As shown in Table 7, the data support H1 and H3 but not H2. Performance Expectancy is associated with higher Learning Experience ($B = 0.502$, $t = 5.697$, $p < 0.001$), while Facilitating Conditions show a smaller positive association with Learning Experience ($B = 0.288$, $t = 3.216$, $p = 0.001$). In contrast, the coefficient for Effort Expectancy is not statistically significant ($B = 0.114$, $t = 0.951$, $p = 0.342$).

The results also support H4 and H5. Learning Experience has a positive association with Digital Engagement ($B = 0.846$, $t = 28.128$, $p < 0.001$) and Digital Integration in Daily Life ($B = 0.793$, $t = 15.581$, $p < 0.001$). Nevertheless, the estimate involving Digital Engagement should be viewed cautiously because Table 4 indicates only marginal empirical separation between the two constructs.

Among the three predictors of Learning Experience, Performance Expectancy has the largest estimated standardized coefficient, followed by Facilitating Conditions and Effort Expectancy. This ordering describes the estimates in the specified model; it does not establish that the coefficients differ significantly from one another. Likewise, the nonsignificant result for Effort Expectancy indicates insufficient evidence to support H2 in this sample rather than demonstrating that ease of LMS use is unimportant.

Four of the five direct hypotheses receive empirical support. These coefficients describe relationships observed in the cross-sectional data and should not be interpreted as evidence of causal effects.

Table 8. Mediation Analysis Results

Hypothesis	Indirect Path	B	t-value	p-value	Decision
H6	Performance Expectancy → Learning Experience → Digital Engagement	0.424	5.574	<0.001	Supported
H7	Performance Expectancy → Learning Experience → Digital Integration in Daily Life	0.398	5.241	<0.001	Supported
H8	Effort Expectancy → Learning Experience → Digital Engagement	0.096	0.945	0.345	Not Supported
H9	Effort Expectancy → Learning Experience → Digital Integration in Daily Life	0.090	0.928	0.353	Not Supported
H10	Facilitating Conditions → Learning Experience → Digital Engagement	0.244	3.228	0.001	Supported
H11	Facilitating Conditions → Learning Experience → Digital Integration in Daily Life	0.228	3.357	0.001	Supported

Table 8 shows that Performance Expectancy has significant indirect associations with both outcomes through Learning Experience. The estimated indirect coefficient is 0.424 for Digital Engagement ($t = 5.574$, $p < 0.001$) and 0.398 for Digital Integration in Daily Life ($t = 5.241$, $p < 0.001$). These findings provide support for H6 and H7.

The corresponding indirect associations originating from Effort Expectancy do not reach statistical significance. Its coefficient is 0.096 for Digital Engagement ($t = 0.945$, $p = 0.345$) and 0.090 for Digital Integration in Daily Life ($t = 0.928$, $p = 0.353$). Thus, the evidence does not support H8 or H9.

Learning Experience also carries significant indirect associations from Facilitating Conditions to the two outcomes. The estimate is 0.244 for Digital Engagement ($t = 3.228$, $p = 0.001$) and 0.228 for Digital Integration in Daily Life ($t = 3.357$, $p = 0.001$). H10 and H11 are therefore supported. In total, the analysis supports four of the six indirect-effect hypotheses.

These findings are consistent with the proposed experiential pathway linking Performance Expectancy and Facilitating Conditions with digital learning practices through Learning Experience. However, direct paths from the three acceptance factors to the two outcomes were not estimated. Consequently, the analysis does not establish whether significant indirect effects coexist with direct relationships and cannot distinguish full, partial, or indirect-only mediation. The omission of direct paths is a model specification decision, not evidence that their effects are zero or statistically nonsignificant.

The indirect effects leading to Digital Engagement also require caution because of the limited empirical separation between Learning Experience and Digital Engagement. Furthermore, the cross-sectional design does not establish the temporal sequence underlying the proposed pathway. The

results therefore support statistical indirect associations within the specified model rather than confirming a causal mediation process.

b) Discussion

The results show that students' Learning Experience varies with the benefits and supporting conditions they perceive when using an LMS. Performance Expectancy and Facilitating Conditions are associated with a more favorable Learning Experience, whereas the data do not establish a significant relationship for Effort Expectancy. Learning Experience is subsequently associated with active digital participation and the routine incorporation of LMS use into academic activities. This pattern is compatible with an experiential connection between selected acceptance factors and students' post-adoption learning practices.

Of the three antecedents, Performance Expectancy has the largest estimated coefficient. Students tend to report a better Learning Experience when they believe that the LMS helps them complete academic work and achieve learning goals. This pattern is consistent with the central role assigned to performance-related benefits in technology acceptance theory ([Venkatesh et al., 2012](#)). The present finding extends that reasoning to an existing-user context by connecting perceived benefit with students' appraisal of learning after adoption. Even so, Performance Expectancy and Learning Experience represent different concepts: one concerns the expected academic value of the system, while the other concerns the experience arising from its use. The reported ordering of coefficients also does not demonstrate that their magnitudes differ significantly.

Facilitating Conditions provide a second explanation for differences in Learning Experience. Students may be better able to concentrate on academic activities when devices, internet access, and technical assistance are available and reliable. The finding therefore draws attention to the practical environment surrounding LMS use, in addition to the value students expect from the platform. However, the construct records students' perceptions of available support; it does not directly assess institutional readiness, organizational capability, or the return obtained from university technology investments.

The nonsignificant relationship between Effort Expectancy and Learning Experience warrants a more qualified interpretation. It indicates that the analysis did not establish a distinct association between perceived ease of use and Learning Experience after accounting for Performance Expectancy and Facilitating Conditions. Familiarity with the LMS offers one possible explanation: usability may be less salient to students who already use the platform for academic activities. However, the study did not directly test whether duration of use moderates this relationship. The result therefore does not demonstrate that usability is unimportant or that its influence necessarily declines with experience. Limited statistical power for smaller effects and overlap among the acceptance-related predictors also remain possible explanations.

Learning Experience is associated with two related but different forms of digital learning practice. Its relationship with Digital Engagement indicates that students who evaluate their experience favorably also tend to participate more actively. Its relationship with Digital Integration in Daily Life indicates that LMS use is more likely to become part of their ordinary academic routines. The two outcomes should not be treated as interchangeable. Students can check materials and announcements routinely without participating intensively, while participation in a particular digital activity does not necessarily make LMS use habitual. The findings therefore concern specific learning practices rather than comprehensive digital culture or competence, consistent with [Ng's \(2012\)](#) distinction between technological familiarity and effective digital literacy.

The indirect-effect findings form the main contribution of the proposed model. Learning Experience carries significant associations from Performance Expectancy and Facilitating Conditions to both digital learning outcomes, whereas the corresponding associations originating from Effort Expectancy are not supported. The study therefore uses selected UTAUT2 constructs to explain an experiential post-adoption process rather than to validate the entire acceptance framework. The LXD perspective contributes by directing attention to how learners experience a designed digital environment ([Jahnke et al., 2022](#)). Together, these perspectives connect students' assessments of the LMS with their learning experiences and subsequent digital practices.

This contribution remains provisional. Direct relationships between the acceptance factors and the two outcomes were not estimated, preventing classification of the mediation pattern or conclusions that Learning Experience is a necessary or exclusive pathway. Moreover, the marginal empirical separation between Learning Experience and Digital Engagement may affect the interpretation of their relationship and the indirect effects involving Digital Engagement. The relatively low estimated-model NFI also limits claims about overall model adequacy. These issues should be considered alongside the statistically significant findings rather than treated as resolved by them.

Practically, the findings suggest that universities should attend to the educational benefits students perceive and the resources supporting LMS-based learning. Clear alignment between LMS activities and course objectives, accessible technical assistance, and reliable access to learning resources are relevant areas for improvement. Instructional design can also emphasize meaningful activities and opportunities for participation. The nonsignificant Effort Expectancy result does not justify neglecting usability, particularly for students facing access or navigation difficulties.

At the institutional level, LMS-generated records may support academic monitoring and evidence-informed decisions, as discussed in the learning analytics literature ([Long & Siemens, 2011](#)). Such records could also inform transparency and accountability practices. However, governance outcomes were not measured in this study, and the findings do not establish improvements in Good University Governance. These possibilities represent broader institutional implications for future investigation.

5) Conclusion

Using survey responses from 114 university students, this study evaluated a post-adoption model that connects LMS acceptance factors, Learning Experience, and two digital learning practices. Performance Expectancy and Facilitating Conditions were associated with a more favorable Learning Experience, whereas Effort Expectancy was not. Learning Experience was also positively related to Digital Engagement and Digital Integration in Daily Life. The indirect associations originating from Performance Expectancy and Facilitating Conditions were significant for both outcomes, while those originating from Effort Expectancy were not supported.

The proposed contribution is an experiential explanation of LMS use after adoption. Rather than testing UTAUT2 in its entirety, the model uses three of its constructs to investigate how students' perceptions of an LMS relate to Learning Experience and, through that experience, to active participation and routine academic use. The results are compatible with this proposed route within the specified model. However, they do not demonstrate that Learning Experience is the only mechanism or an indispensable mediator of these relationships.

Practically, universities should consider students' perceived educational benefits and access to supporting resources when improving LMS-based learning. Aligning digital activities with course objectives, providing accessible technical assistance, and supporting meaningful participation are relevant priorities. The nonsignificant Effort Expectancy result does not imply that usability can be neglected; it indicates that its proposed relationship with Learning Experience was not supported in this sample. Broader implications for institutional monitoring and governance remain possibilities for future investigation rather than empirically demonstrated outcomes.

The findings must be considered within several limitations. Because all variables were measured through self-reports at one point in time, their temporal sequence and causal direction cannot be established, and common method influence remains possible. The use of purposive sampling further restricts generalization beyond the participants. Moreover, women represented 93.86% of the sample, meaning that the results may not reflect student populations with substantially different gender compositions.

Additional limitations arise from the measurement and structural specification. Although the Fornell-Larcker requirement is met numerically, the square root of AVE for Digital Engagement differs from its correlation with Learning Experience by only 0.001. Because HTMT was unavailable, the empirical separation of these constructs remains uncertain. The estimated-model NFI also provides limited support for overall fit, while indicator VIF values cannot establish whether collinearity is absent among structural predictors. In addition, the model excludes direct paths from the acceptance factors to the two outcomes, preventing identification of the mediation pattern. The reported Q^2 values should likewise not be treated as evidence of predictive accuracy for new samples or institutions.

Further studies should collect predictor and outcome measures at different times or employ longitudinal designs. Self-reported responses could also be combined with LMS activity records, and the sample should include a more varied group of students. More rigorous assessment of construct separation, structural collinearity, direct relationships, and out-of-sample prediction would provide a stronger test of the proposed model.

Statement on the Use of Generative Artificial Intelligence (AI)

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) and Grammarly solely to support language editing, grammar correction, clarity, and readability. All AI-assisted content was critically reviewed, revised, and validated by the authors. These tools were not used as authors or as substitutes for scientific judgment, data analysis, interpretation of findings, or the formulation of conclusions. The authors take full responsibility for the accuracy, originality, integrity, and final content of the manuscript. This disclosure complies with the journal's [Policy on the Use of Generative Artificial Intelligence \(GenAI\)](#).

References :

- Abdelfattah, F., Al Mashaikhya, N. Y., Dahleez, K. A., & El Saleh, A. (2024). A systematic review of e-learning systems adoption before and during the COVID-19. *Global Knowledge, Memory and Communication*, 73(3), 292-311. <https://doi.org/10.1108/GKMC-02-2022-0033>
- Alkhateeb, M. A., & Abdalla, R. A. (2021). Factors influencing student satisfaction towards using learning management system Moodle. *International Journal of Information and Communication Technology Education*, 17(1), 138-153. <https://doi.org/10.4018/IJICTE.2021010109>
- Al-Samarraie, H., Selim, H., Teo, T., & Zaqout, F. (2017). Isolation and distinctiveness in the design of e-learning systems influence user preferences. *Interactive Learning Environments*, 25(4), 452-466. <https://doi.org/10.1080/10494820.2016.1138313>
- Drugova, E., Zhuravleva, I., Zakharova, U., & Latipov, A. (2024). Learning analytics driven improvements in learning design in higher education: A systematic literature review. *Journal of Computer Assisted Learning*, 40(2), 510-524. <https://doi.org/10.1111/jcal.12894>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149-1160. <https://doi.org/10.3758/BRM.41.4.1149>
- Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic review. *British Journal of Educational Technology*, 50(5), 2572-2593. <https://doi.org/10.1111/bjet.12864>
- Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), Article 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Jahnke, I., Schmidt, M., Earnshaw, Y., & Tawfik, A. A. (2022). Theoretical considerations of learning experience design. In H. Leary, S. P. Greenhalgh, K. B. Staudt Willet, & M.-H. Cho (Eds.), *Theories to influence the future of learning design and technology: 2021 AECT RTD theory spotlight competition*. EdTech Books. https://edtechbooks.org/theory_comp_2021/toward_theory_of_LXD_jahnke_earnshaw_schmidt_tawfik
- Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30-40. <https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education>
- Mella-Norambuena, J., Chiappe, A., & Badilla-Quintana, M. G. (2025). Theoretical and empirical models underlying the teaching use of LMS platforms in higher education: A systematic review. *Journal of Computers in Education*, 12(3), 997-1023. <https://doi.org/10.1007/s40692-024-00336-9>
- Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education*, 59(3), 1065-1078. <https://doi.org/10.1016/j.compedu.2012.04.016>
- Paulsen, L., & Lindsay, E. (2024). Learning analytics dashboards are increasingly becoming about learning and not just analytics: A systematic review. *Education and Information Technologies*, 29(11), 14279-14308. <https://doi.org/10.1007/s10639-023-12401-4>
- SmartPLS. (n.d.). *Model fit*. <https://www.smartpls.com/documentation/algorithms-and-techniques/model-fit/>
- van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2019). Determinants of 21st-century digital skills: A large-scale survey among working professionals. *Computers in Human Behavior*, 100, 93-104. <https://doi.org/10.1016/j.chb.2019.06.017>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178. <https://doi.org/10.2307/41410412>
- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28(2), 118-144. <https://doi.org/10.1016/j.jsis.2019.01.003>
- Wahyudin, A., Nurkhin, A., & Kiswanto. (2017). Hubungan good university governance terhadap kinerja manajemen keuangan perguruan tinggi. *Jurnal Keuangan dan Perbankan*, 21(1), 60-69. <https://doi.org/10.26905/jkdp.v21i1.1227>
- Xue, L., Rashid, A. M., & Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. *SAGE Open*, 14(1). <https://doi.org/10.1177/21582440241229570>

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. *Education and Information Technologies*, 30(9), 12015-12053. <https://doi.org/10.1007/s10639-024-13299-2>