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Research Article

Acceptance and use of online learning environments in higher education: Scale development and UTAUT model testing

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This study examined the acceptance and use of online learning environments among higher education students through the lens of the Unified Theory of Acceptance and Use of Technology. Drawing on a sample of 959 university students, the study developed and psychometrically evaluated a new Online Learning Environments Acceptance and Use Scale and tested the hypothesized structural model. Confirmatory factor analysis with robust maximum likelihood estimation supported a five-factor acceptance structure comprising performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention, with actual use modeled as a separate behavioral criterion. The five acceptance factors showed strong convergent validity, reliability, and discriminant validity, and the measurement model demonstrated adequate fit. In the structural model, performance expectancy, social influence, and effort expectancy each significantly predicted behavioral intention, with performance expectancy as the dominant predictor. Facilitating conditions significantly predicted actual use, whereas the path from behavioral intention to actual use was non-significant. Findings are interpreted in light of the mandatory nature of the online-only courses examined, in which students had no face-to-face alternative, and contribute a psychometrically evaluated, context-sensitive instrument to the technology acceptance literature.

Keywords: Higher education; Online learning environments; Structural equation modeling; Technology acceptance; UTAUT

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1. Introduction

Between 2020 and 2022, higher education institutions worldwide faced an abrupt and near-total shift to online learning environments [OLE], compressing a decade of incremental digital adoption into a matter of weeks (Almaiah et al., 2020). In Türkiye, where the Council of Higher Education [CoHE] coordinated a nationwide transition to distance delivery across its public and private universities, this shift imposed online learning on students regardless of prior motivation, digital familiarity, or personal preference. The scale and involuntary character of this transition created conditions that challenge several foundational assumptions of technology acceptance theory, most notably the assumption that individuals' motivational states freely determine their use behavior. Although this large-scale shift was initially a temporary emergency response, online course

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delivery has since become a durable feature of higher education in many institutions, sustaining conditions of compulsory online learning well beyond the initial transition (Cobo-Rendón et al., 2022; Lockee, 2021).

The Unified Theory of Acceptance and Use of Technology [UTAUT; Venkatesh et al., 2003] remains the most comprehensive framework for modeling technology acceptance across organizational and educational settings. By synthesizing eight predecessor models, UTAUT identifies four core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) as determinants of behavioral intention and actual use, and the framework has been validated across hundreds of studies in diverse cultural and technological contexts (Williams et al., 2015). Yet its application to educational technology has largely proceeded without critically engaging a key moderating condition: voluntariness of use. When adoption is mandated, the theoretical relationship between intention and behavior is predicted to weaken or disappear (Venkatesh et al., 2003), a claim the literature affirms but that remains empirically underexamined in higher education settings (Lehmann et al., 2023).

Two further gaps persist. First, instruments used in UTAUT-based e-learning research have predominantly been adapted from organizational IT contexts, transferring item content that may not adequately reflect the student experience of academic technology use (Al-Nuaimi & Al-Emran, 2021; Xue et al., 2024). Second, most studies test only the partial UTAUT chain (predictors of behavioral intention) while omitting actual use behavior, leaving the full theoretical model without empirical test (Al-Nuaimi & Al-Emran, 2021). Instrument mismatch and truncated models each limit the cumulative validity of the literature.

The present study addresses these gaps by validating an Online Learning Environments Acceptance and Use Scale developed in the present study grounded in UTAUT construct definitions and appropriate for the student learning context, and by testing the complete UTAUT structural model, from predictors of intention through to actual use behavior, in a large sample of Turkish university students enrolled in courses delivered exclusively online, for which no face-to-face option was available.

2. UTAUT: Theoretical Foundations

The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) was constructed through a synthesis of eight established technology acceptance models, including the Theory of Reasoned Action, the Technology Acceptance Model (Davis, 1989), the Theory of Planned Behavior (Ajzen, 1991), and the Motivational Model. The result was a parsimonious framework in which four constructs (performance expectancy, the degree to which a technology is believed to enhance task performance; effort expectancy, the perceived ease of using the technology; social influence, the degree to which significant others believe the user should adopt the technology; and facilitating conditions, the degree to which organizational and technical infrastructure supports use) account for substantial variance in behavioral intention and actual use. Across its original validation studies, the four-factor UTAUT model explained approximately 70% of variance in intention and 50% in use (Venkatesh et al., 2003).

A systematic literature review of 174 empirical UTAUT studies (Williams et al., 2015) confirmed the framework's explanatory robustness across contexts while identifying critical boundary conditions. Voluntariness of use emerged as the most consistent moderator: performance expectancy, effort expectancy, and social influence each showed stronger predictive effects under voluntary than mandatory conditions, while facilitating conditions were more predictive when use was institutionally required. This moderating pattern carries direct implications for the educational technology context, particularly in settings where online learning is compulsory rather than elective.

UTAUT2 (Venkatesh et al., 2012) extended the original model to consumer contexts by adding hedonic motivation, habit, and price value as predictors, with age, gender, and experience as moderators. Although UTAUT2 has been applied in educational technology research, its

additional constructs are less theoretically appropriate for institutional e-learning settings where use is non-optional and instructional costs are borne by the institution. Dwivedi et al. (2019), reviewing accumulated UTAUT evidence, advocated for a theoretically revised model that better accounts for contextual variation in path strengths, particularly the attenuated social influence effect under mandatory conditions and the diminishing salience of effort expectancy as user experience accrues.

2.1. UTAUT in E-Learning Contexts

Applications of UTAUT in e-learning have been numerous and geographically diverse, and systematic reviews of this body of work document consistent patterns alongside persistent gaps. Xue et al. (2024), in a systematic review of 162 SSCI/SCI-E articles applying UTAUT in higher education from 2008 to 2022, found that performance expectancy consistently emerged as the strongest predictor of behavioral intention across studies and disciplinary contexts, while the relative contributions of effort expectancy and social influence varied with institutional culture, technology type, and learner characteristics. Al-Nuaimi and Al-Emran (2021), reviewing 68 studies on learning management systems [LMS] and technology acceptance models, found that UTAUT and its variants dominated the theoretical landscape but that most studies adapted general-purpose instruments without context-specific validation, a practice that may inflate standardized path coefficients through shared method variance and reduce generalizability across educational settings. In a complementary systematic review of technology acceptance research in mobile learning, Al-Emran et al. (2018) similarly observed that facilitating conditions and social influence were among the most frequently examined determinants, while methodological inconsistencies in instrument adaptation limited cross-study comparability.

Individual study findings corroborate these patterns. Samsudeen and Mohamed (2019) reported that performance expectancy, effort expectancy, and facilitating conditions significantly predicted e-learning use among Sri Lankan university students, with performance expectancy accounting for the largest proportion of variance. In a comparable higher education setting, Park (2009) found that perceived usefulness was the strongest determinant of university students' behavioral intention to use e-learning, paralleling the consistent primacy of performance-related beliefs across acceptance models. More recently, Sifundza and Utete (2023) reported comparatively low levels of online learning adoption among students at an emerging South African institution, underscoring that adoption levels vary substantially across higher education contexts. Abbad (2021) confirmed the salience of performance expectancy and effort expectancy for Moodle adoption among Jordanian undergraduates while finding social influence non-significant, a pattern consistent with the tendency for social referents to matter less when the technology decision is institutionally constrained rather than individually discretionary. In MOOC contexts, where enrollment remains voluntary, Fianu et al. (2018) found facilitating conditions and perceived usefulness to be consistent adoption drivers, underscoring the role of access and resource support in behavioral translation.

The large-scale shift to online instruction prompted by the COVID-19 pandemic created a natural experiment in mandatory technology adoption. As institutions globally suspended face-to-face instruction, online learning transitioned from an elective modality to an institutional requirement for millions of students (Almaiah et al., 2020; Wangdi et al., 2021). Almaiah et al. (2020) found that infrastructure barriers (device access, connectivity, and technical support) emerged as the primary discriminators between successful and unsuccessful OLE adoption during the pandemic, with motivational attitudes playing a secondary role. This pattern inverts the standard UTAUT prediction in which intention (driven by motivational attitudes) is the primary behavioral antecedent, and is consistent with the theoretical claim that voluntary use is a prerequisite for motivational predictors to drive behavioral frequency.

Lehmann et al. (2023), in a study explicitly designed to test UTAUT under compulsory digital learning conditions, found that institutional facilitation rather than individual motivation became

the primary driver of use when adoption was mandated. Their structural model showed a substantially attenuated and non-significant path from behavioral intention to actual use, a result the present study replicates in an independent Turkish sample. Zheng et al. (2025), in a meta-analytic review of 91 COVID-period e-learning studies using UTAUT2, found that the effect of performance expectancy on behavioral intention was stronger under mandatory than voluntary conditions, consistent with the interpretation that perceived academic utility remains motivationally active even when it does not determine whether use occurs. In Turkish higher education specifically, Ciftci et al. (2023) examined UTAUT2 among 708 medical educators during mandatory pandemic-era distance education and reported that facilitating conditions and habit were the dominant predictors of actual use, while the behavioral intention–use path was weak relative to voluntary-use benchmarks.

Together, these findings converge on the voluntariness moderation account articulated in the original UTAUT: when use is not discretionary, the intention–behavior link is moderated toward zero because individual motivational states no longer determine whether use occurs: institutional mandates and facilitating conditions do.

A persistent methodological concern in UTAUT-based e-learning research is the uncritical adaptation of instruments designed for organizational IT contexts. Items originally developed to measure performance expectancy in enterprise software use (referencing "productivity," "job performance," or "work effectiveness") map imperfectly onto students' experiences of OLEs, where the relevant performance domain is academic achievement, cognitive engagement, and learning outcome (Al-Nuaimi & Al-Emran, 2021). Facilitating conditions items referencing "IT support departments" similarly miss the student experience of institutional LMS infrastructure. Such construct-context mismatches introduce validity threats that statistical corrections cannot resolve.

Appropriate practice calls for theoretically grounded item generation from source construct definitions (Venkatesh et al., 2003), content validity assessment by domain experts, pilot testing prior to the main study, and a confirmatory, rather than purely exploratory, factor analysis strategy in the main validation sample. These standards are inconsistently applied in the UTAUT-in-e-learning literature. The absence of a validated, context-specific instrument appropriate for Turkish higher education students represents a concrete gap the present study addresses.

Higher education in Türkiye is organized under CoHE oversight. Following the widespread adoption of online delivery across Turkish universities, a subset of courses has come to be offered exclusively online, with no face-to-face alternative, making online learning environments a compulsory rather than elective component of students' academic experience in these courses. Existing Turkish applications of UTAUT in educational technology have been largely domain-specific: Tosuntaş et al. (2015) applied UTAUT to interactive whiteboard adoption under the FATIH Project, and Ciftci et al. (2023) examined distance education acceptance among medical educators. A validated, general-purpose OLE acceptance instrument appropriate for the broader Turkish undergraduate population remains scarce in the literature.

2.2. The Present Study

The primary aim of this study was to examine how the core UTAUT relationships (particularly the behavioral intention–actual use link) operate under compulsory online learning conditions. To pursue this aim in a context-appropriate manner, the study also (a) developed and validated a context-specific Online Learning Environments Acceptance and Use Scale grounded in UTAUT construct definitions, and (b) tested the complete UTAUT structural model, from predictors of behavioral intention through to actual use behavior, in a Turkish university sample under mandatory online learning conditions. Five structural hypotheses were advanced.

H_1: *Performance expectancy positively predicts behavioral intention.* Performance expectancy, the degree to which students believe OLEs help them achieve academic outcomes, has consistently emerged as the strongest predictor of behavioral intention in UTAUT-based e-learning research (Venkatesh

et al., 2003; Xue et al., 2024). This effect is expected to be robust in a mandatory-use context: even when students cannot choose whether to use an OLE, they form differentiated beliefs about whether the system will support their academic goals, and those beliefs shape motivational orientation.

H_2: *Effort expectancy positively predicts behavioral intention.* Effort expectancy, perceived ease of OLE use, is a theorized secondary predictor of intention (Venkatesh et al., 2003), with its antecedents traced to users' general computer self-efficacy and accumulated system experience (Venkatesh & Davis, 1996). Its effect diminishes as experience accrues (Dwivedi et al., 2019), but in a sample spanning diverse levels of digital experience and LMS familiarity, variation in perceived ease is expected to retain a modest but significant predictive contribution.

H_3: *Social influence positively predicts behavioral intention.* Social influence captures the degree to which students perceive that instructors, peers, and significant others expect them to engage with OLEs. Under mandatory conditions, social influence is theorized to exert a weaker effect on intention than under voluntary conditions (Venkatesh et al., 2003; Williams et al., 2015); indeed, Teo (2011) found subjective norm to be a non-significant predictor of teachers' technology use intention even as other acceptance constructs remained influential. Nevertheless, given that the Turkish higher education context affords instructors considerable authority over students' academic self-regulation, a meaningful, if attenuated, social influence effect is expected.

H_4: *Facilitating conditions positively predict actual use.* Facilitating conditions, defined as access to devices, connectivity, technical support, and instructional resources, are theorized to predict actual use behavior directly, bypassing the intention pathway (Venkatesh et al., 2003). Under mandatory conditions, differential access to facilitating resources becomes the primary discriminator between those who use the system frequently and fluently and those who do not.

H_5: *Behavioral intention positively predicts actual use.* Although the original UTAUT specifies a positive intention–use path, it simultaneously identifies voluntariness as a key moderator of this relationship. Under mandatory conditions, behavioral intention is expected to be a weaker predictor of actual use than in voluntary settings, because students use OLEs regardless of prior intention when institutional mandates remove the exercise of choice. This hypothesis is tested as a formal directional prediction while acknowledging the theoretical expectation of attenuation.

3. Method

3.1. Research Design

This study employed a cross-sectional, correlational design using quantitative survey data. Structural equation modeling [SEM] was used to develop and psychometrically evaluate a measurement instrument and to test the hypothesized relationships among the UTAUT constructs. Because all variables were measured at a single time point, the analyses support predictive and associational rather than causal interpretations.

3.2. Participants

Participants were 959 students enrolled at a large state university in Türkiye. The sample comprised 718 women (74.9%) and 241 men (25.1%), with a mean age of 22.1 years (SD = 4.3, range = 18–58). Data were collected from students enrolled in courses that were delivered exclusively through online learning environments, with no face-to-face option. For these compulsory courses, use of the institutional online learning environment was therefore mandatory rather than voluntary.

Participants were recruited through convenience sampling, via an announcement inviting voluntary participation in an online survey. The sample size was well suited to the scale development aim: with 24 candidate items, the 959 respondents yield a respondent-to-item ratio of approximately 40:1, substantially exceeding the minimum ratios commonly recommended for factor-analytic scale development (DeVellis, 2016; Hair et al., 2019).

3.3. Procedure

Data were collected through an online survey delivered via the institution's learning management system at the midpoint of the semester, by which time students had already been using the online learning environment for their courses for several weeks. Their reports of actual use therefore reflected accumulated rather than anticipated experience with the system. Participation was voluntary, and informed consent was obtained from all participants before data collection began.

3.4. Measures

Demographic and personal information form: Participants reported their age, gender, department, and year of study, together with the device they most frequently used to access online learning environments (desktop computer, laptop, tablet, or smartphone).

Online Learning Environments Acceptance and Use Scale: Technology acceptance and use were assessed using the Online Learning Environments Acceptance and Use Scale, which was developed and psychometrically evaluated in the present study within the UTAUT framework (Venkatesh et al., 2003) (see Appendix 1). The scale provides a context-specific operationalization of UTAUT's five acceptance constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention) within the student online learning context. An initial pool of 24 items was generated, and item development proceeded in three stages. First, the theoretical domain of each construct was defined, and items were developed by adapting the original UTAUT scales (Venkatesh et al., 2003), which are designed as generic templates intended to be tailored to a specific target technology. Following the construct-driven approach recommended by Hinkin (1998), each item was reworded to reflect students' academic experience of online learning environments rather than organizational IT use, while preserving the conceptual content of the original constructs. For example, performance expectancy items referenced students' beliefs about academic achievement and learning outcomes rather than job productivity; facilitating conditions items referenced device access, connectivity, and institutional LMS support services rather than general IT departments. Second, the item pool was reviewed by a panel of three educational technology specialists who assessed content validity and clarity; based on their qualitative consensus, items were refined for wording and conceptual fit, with no items removed at this stage. Third, the items were administered in a small pilot to check clarity and comprehension, and minor wording revisions were made prior to the main data collection. Following the confirmatory factor analysis [CFA] (reported in the Results), five items were removed because they exhibited problematic psychometric characteristics (standardized factor loadings below the acceptable threshold and evidence of local dependency with adjacent items within their subscales): two from facilitating conditions, two from social influence, and one from performance expectancy. These removals were part of the measurement model evaluation and not post hoc modifications to fit; no error covariances were freed at any stage. The final 19-item scale comprised performance expectancy [PE] (5 items; e.g., "Online learning environments are useful in my learning process"), effort expectancy [EE] (4 items; e.g., "Online learning environments are simple to use and easy to understand"), social influence [SI] (4 items; e.g., "The administrators at my university support my use of online learning environments"), facilitating conditions [FC] (3 items; e.g., "I have the resources necessary to learn to use online learning environments"), and behavioral intention [BI] (3 items; e.g., "I intend to use online learning environments in the future"), each rated on a 7-point Likert scale from 1 (*strongly disagree*) to 7 (*strongly agree*).

Actual use: Actual use of online learning environments was measured as a composite index computed from three ordinal behavioral self-report items capturing weekly frequency of use, weekly hours of use, and approximate minutes of use per class session. The three items were combined into a single actual-use score, which was modeled as a single behavioral criterion distinct from the 7-point Likert acceptance items.

3.5. Data Analysis

Confirmatory factor analysis and structural equation modeling were conducted to evaluate the measurement and structural models, following the two-step modeling strategy recommended by Anderson and Gerbing (1988) of establishing measurement model adequacy prior to testing structural paths. Because Mardia's (1970) coefficient indicated a violation of multivariate normality (z = 105.72), parameters were estimated using maximum likelihood estimation with robust [MLR] standard errors and Satorra–Bentler scaled test statistics (Satorra & Bentler, 1994); robust versions of the CFI, TLI, and RMSEA are reported. Model fit was evaluated using the comparative fit index [CFI], the Tucker–Lewis index [TLI], the root mean square error of approximation [RMSEA], the standardized root mean square residual [SRMR], and the chi-square statistic, interpreted in light of established thresholds (Hu & Bentler, 1999). Convergent validity was assessed via average variance extracted [AVE] and composite reliability [CR], and discriminant validity via the heterotrait–monotrait ratio of correlations [HTMT] (Henseler et al., 2015). Reliability was estimated using McDonald's omega (McDonald, 1999) and Cronbach's alpha.

Because all study variables were collected from the same respondents in a single, cross-sectional survey administration, several procedural remedies were applied during data collection to reduce susceptibility to common method variance (Podsakoff et al., 2003): respondents were assured of full anonymity, items from different constructs were interspersed throughout the questionnaire, and the actual use items were positioned at the end of the survey to reduce semantic proximity with the attitudinal predictors. The implications of the cross-sectional, single-source design are considered further in the Limitations section.

4. Results

4.1. Descriptive Statistics and Correlations

The means, standard deviations, and bivariate correlations among the study variables are presented in Table 1. Facilitating conditions showed the highest mean rating (M = 5.49) and actual use the lowest (M = 3.57). The correlations among the acceptance constructs were moderate to strong, ranging from .31 to .77, with the strongest association between performance expectancy and behavioral intention (r = .77). Actual use correlated only weakly with all other variables, with correlations ranging from .11 to .22.

Table 1
Means, Standard Deviations, and Correlations Among Study Variables

Variable	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*
1. Performance expectancy	4.34	1.74	—					
2. Effort expectancy	5.04	1.54	.57	—				
3. Social influence	4.85	1.44	.53	.51	—			
4. Facilitating conditions	5.49	1.40	.31	.66	.45	—		
5. Behavioral intention	4.65	1.79	.77	.53	.53	.39	—	
6. Actual use	3.57	1.28	.11	.14	.22	.16	.12	—

Note. All correlations ≥ .11 are significant at $p < .01$. N = 959.

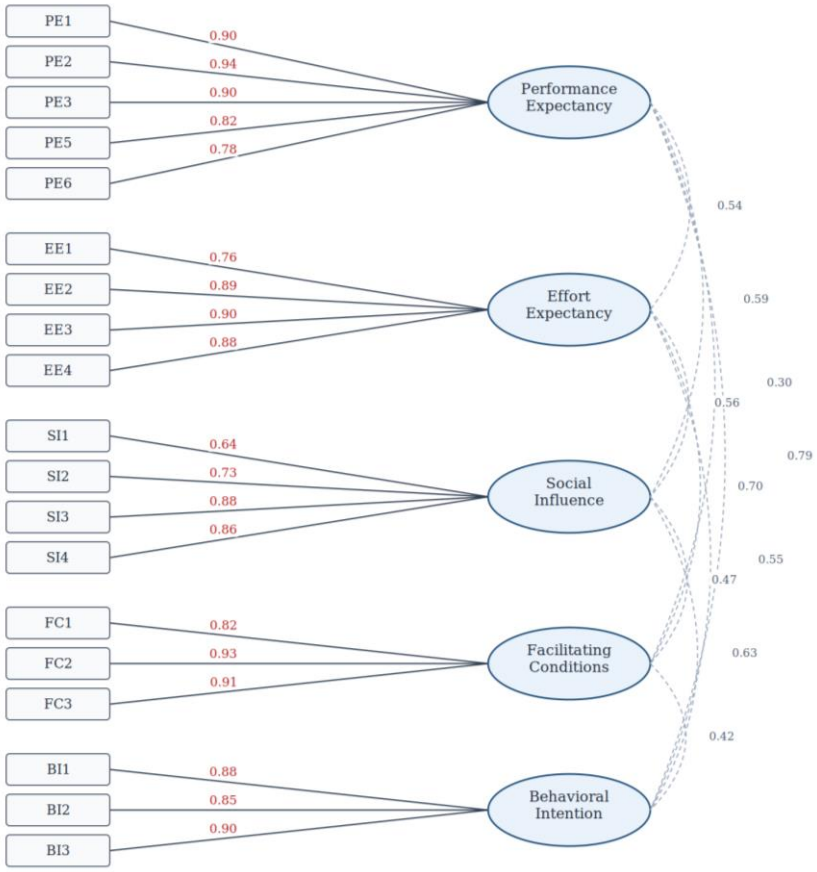
4.2. Measurement Model

Prior to testing the structural model, the measurement model was evaluated. As described in Section 3.4 (Measures), five items were removed following CFA-based item analysis (two from facilitating conditions, two from social influence, and one from performance expectancy) yielding a 19-item, five-factor solution. To preserve the integrity of the confirmatory approach, no post hoc error covariances were freed; the model was tested in its theoretically specified form. The resulting model demonstrated acceptable fit, $\chi^2_{SB}(142, N = 959) = 918.44$, $\chi^2_{SB}/df = 6.47$, CFI = .931, TLI = .917, robust RMSEA = .090, 90% CI [.085, .096], SRMR = .065. The measurement model RMSEA of .090 marginally exceeds the .08 threshold; however, CFI = .931 and TLI = .917 both satisfy the ≥ .90 criterion, and with N = 959 and 142 degrees of freedom the chi-square statistic, and indices derived

from it, are sensitive to minor, theoretically trivial misspecification (Hu & Bentler, 1999). The χ^2_{SB}/df ratio of 6.47, while above the conventional cutoff of 5.0, is likewise consistent with the well-documented large-sample inflation of chi-square-based statistics. The standardized factor loadings and interfactor correlations are displayed in Figure 1.

Figure 1

Standardized Measurement Model (Confirmatory Factor Analysis) of the Online Learning Environments Acceptance and Use Scale



Note. All standardized factor loadings were statistically significant ($p < .001$). Dashed arcs represent interfactor correlations, $N = 959$.

Figure 1 displays the standardized measurement model, showing that all items loaded substantially on their intended latent factors.

As shown in Table 2, all standardized factor loadings exceeded the recommended threshold, and all factors demonstrated strong convergent validity and reliability, with AVE ranging from .61 to .78, CR from .86 to .94, and McDonald's omega from .86 to .94.

Table 2

Standardized Factor Loadings, Convergent Validity, and Reliability for the Measurement Model

Factor	*Items*	*λ range*	*AVE*	*CR*	*ω*	α
Performance expectancy	5	.78–.94	.754	.939	.939	.935
Effort expectancy	4	.76–.90	.731	.919	.919	.914
Social influence	4	.64–.88	.614	.861	.861	.863
Facilitating conditions	3	.82–.93	.784	.916	.916	.911
Behavioral intention	3	.85–.90	.769	.909	.909	.908

Note. λ = standardized factor loading; AVE = average variance extracted; CR = composite reliability; ω = McDonald's omega; α = Cronbach's alpha. Estimates are based on MLR estimation. $N = 959$.

Discriminant validity was supported using the heterotrait–monotrait ratio of correlations (HTMT; Henseler et al., 2015; see Table 3), as all HTMT values fell below the .85 criterion, with the

highest value observed between performance expectancy and behavioral intention (HTMT = .828), consistent with their strong theoretical relationship.

Table 3
Heterotrait–Monotrait Ratio of Correlations Matrix

	PE	*EE*	*SI*	*FC*	*BI*
Performance expectancy	—				
Effort expectancy	.606	—			
Social influence	.576	.569	—		
Facilitating conditions	.333	.718	.509	—	
Behavioral intention	.828	.568	.589	.430	—

Note. All values are below the .85 criterion, supporting discriminant validity. N = 959.

4.3. Structural Model

The hypothesized UTAUT structural model demonstrated acceptable fit, $\chi^2_{SB}(198, N = 959) = 1156.63$, $\chi^2_{SB}/df = 5.84$, CFI = .928, TLI = .916, robust RMSEA = .081, 90% CI [.077, .086], SRMR = .065. Here the RMSEA of .081 sits just above the .08 benchmark, but two considerations support treating the model as adequately specified. First, with N = 959 and 198 degrees of freedom, fit statistics derived from the model chi-square remain sensitive to trivial misspecification, while CFI and TLI both stay within acceptable ranges. Second, the lower bound of the RMSEA confidence interval (.077) falls below .08, indicating that values consistent with adequate fit are plausible for these data.

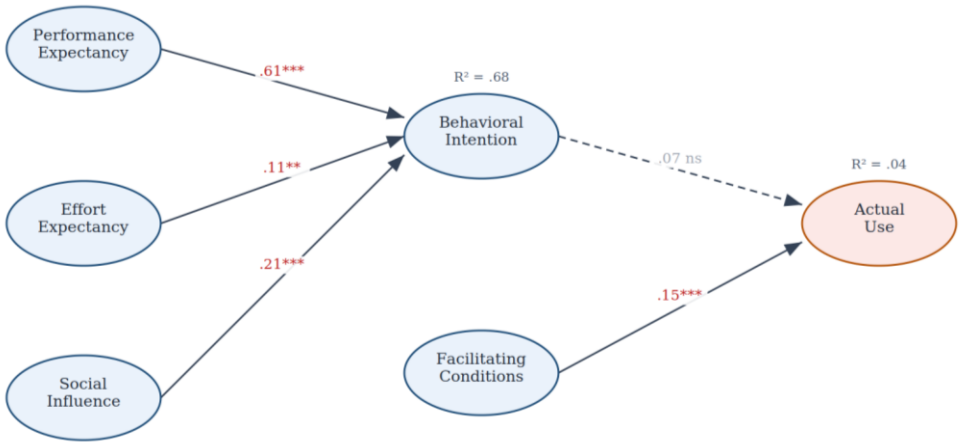
As summarized in Table 4 and depicted in Figure 2, performance expectancy (β = .61, p < .001), social influence (β = .21, p < .001), and effort expectancy (β = .11, p = .004) each significantly

Table 4
Standardized Path Coefficients for the Structural Model

Path	*β*	*p*	*Result*	*Hypothesis*
PE → Behavioral intention	.61	< .001	Supported	H1
EE → Behavioral intention	.11	.004	Supported	H2
SI → Behavioral intention	.21	< .001	Supported	H3
FC → Actual use	.15	< .001	Supported	H4
BI → Actual use	.07	.103	Not supported	H5

Note. PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; BI = behavioral intention. β = standardized coefficient. N = 959.

Figure 2
Standardized Structural Model of Acceptance and Use of Online Learning Environments



Note. The values represent standardized coefficients. *** p < .001, ** p < .01, ns = non-significant. Dashed lines = non-significant paths. N = 959.

predicted behavioral intention, together explaining 67.5% of its variance. H1, H2, and H3 were therefore supported. Facilitating conditions significantly predicted actual use ($\beta = .15$, $p < .001$), supporting H4. The path from behavioral intention to actual use was not statistically significant ($\beta = .07$, $p = .103$), and H5 was not supported. The structural model explained 3.5% of the variance in actual use.

As shown in Figure 2, the structural model illustrates the strong paths from the acceptance constructs to behavioral intention alongside the weak, non-significant path from intention to actual use.

5. Discussion

This study developed and psychometrically evaluated a new instrument for assessing acceptance and use of online learning environments and tested the complete UTAUT structural model among higher education students under mandatory online learning conditions. The measurement model demonstrated strong psychometric properties, and the structural results supported four of the five hypothesized paths. The findings simultaneously confirm UTAUT's core motivational architecture and qualify its behavioral prediction: the theory's motivational constructs robustly predict students' intention to engage with OLEs, but under mandatory-use conditions, that intention does not reliably translate into differential use behavior.

The psychometric evidence supports the usability of the OLEAUS as a measurement tool for OLE acceptance. The five acceptance factors demonstrated strong convergent validity (AVE = .61–.78) and reliability (CR = .86–.94), and discriminant validity was supported by the HTMT criterion, indicating that the instrument distinguishes the UTAUT constructs adequately in this context. At the same time, two features warrant caution in application: the measurement model's RMSEA fell marginally above the conventional threshold, and the facilitating conditions and behavioral intention factors are each measured by three indicators, which, while sufficient for identification, offer limited redundancy. Researchers adopting the instrument may therefore wish to supplement these two subscales with additional indicators. On balance, the evidence indicates that the OLEAUS provides a psychometrically sound, context-appropriate basis for measuring OLE acceptance.

Performance expectancy was by a wide margin the dominant predictor of behavioral intention, accounting for the largest share of the 67.5% of intention variance explained by the model. This finding is consistent with the established pattern in the literature. Xue et al.'s (2024) systematic review of 162 SSCI/SCI-E articles found performance expectancy to be the most consistent and strongest predictor of behavioral intention across UTAUT-based higher education studies, and the coefficient observed here places the present study at the upper end of that distribution. The finding's theoretical implication in a mandatory context is worth underscoring: even when students cannot choose whether to use an OLE, they form differentiated beliefs about whether the system will support their academic goals, and those differentiated beliefs shape motivational orientation. Students who perceive their institution's OLE as academically useful, as likely to help them achieve better learning outcomes, complete assessments, and understand course material, report stronger intentions to engage with it actively, even when engagement is required. This suggests that performance expectancy functions not merely as an adoption signal, but as a predictor of quality of engagement.

Social influence and effort expectancy each contributed significantly, supporting H2 and H3. Social influence's significant contribution, despite the theoretical prediction that it weakens under mandatory conditions (Venkatesh et al., 2003; Williams et al., 2015), may reflect the Turkish higher education context, in which instructors carry substantial normative authority over students' academic self-regulation. Students who perceived that their instructors and peers expected meaningful OLE engagement reported stronger personal intentions to do so. The magnitude of this effect was smaller than performance expectancy's contribution, consistent with the moderated prediction, but non-trivial. Effort expectancy's modest contribution aligns with theoretical

expectations for a population already mandated into OLE use: perceived ease of use plays a secondary motivational role when the option of non-use is unavailable. The contribution is nonetheless significant, likely reflecting genuine variation in prior digital experience, device adequacy, and LMS familiarity across students in the sample.

Facilitating conditions significantly predicted actual use ($\beta = .15$, $p < .001$), supporting H4 and confirming the direct path specified in the structural model. Rather than capturing students' motivational orientation toward the technology, facilitating conditions capture the material conditions that make sustained use possible: device availability, connectivity reliability, and responsiveness of institutional technical support. Under mandatory conditions, it is these material conditions, not motivational states, that differentiate heavier from lighter users.

This interpretation is consistent with Almaiah et al. (2020), who found infrastructure barriers to be the primary discriminators between successful and unsuccessful OLE adoption during the pandemic, and with Ciftci et al.'s (2023) finding that facilitating conditions were a dominant predictor of actual use among Turkish educators navigating mandatory distance teaching. The result has a clear institutional implication: universities seeking to promote equitable and effective OLE engagement should direct resources toward infrastructure access (device lending programs, campus connectivity investments, and scalable technical support) rather than toward attitudinal campaigns that are likely to have limited marginal impact when motivation is already positive and use is required.

The non-significant path from behavioral intention to actual use ($\beta = .07$, $p = .103$) is the study's most theoretically consequential finding and warrants interpretation that extends beyond the observation of non-significance.

The original UTAUT model explicitly theorizes voluntariness of use as a moderator of the intention–behavior relationship (Venkatesh et al., 2003). When use is voluntary, individuals with stronger intentions translate those intentions into greater use frequency and duration. When use is mandated, this mechanism is short-circuited: the institutional requirement ensures that nearly all students use the system irrespective of their prior motivational states, eliminating the behavioral variance that intention would otherwise predict. Venkatesh et al. (2003, p. 455) anticipated this pattern directly, noting that "when use is mandatory, there is little variance to be explained in usage.". Voluntariness has also received renewed empirical attention in recent higher education research; for instance, Han et al. (2025) examined voluntariness of use as a moderator within an extended UTAUT model of technology adoption among university students, underscoring the continuing relevance of this boundary condition.

The present finding is consistent with this theoretical prediction, though it does not itself test the moderation empirically, since all participants were observed under mandatory conditions. This non-significance is consistent with Lehmann et al.'s (2023) demonstration that compulsory digital learning attenuates the intention–use pathway, and with Ciftci et al.'s (2023) report of a weak intention–use path under mandatory Turkish pandemic-era distance education. Patil and Undale (2023), testing an extended UTAUT model among university students who had been compelled to adopt e-learning platforms during the pandemic, similarly found that availability of resources, a facilitating conditions analog, rather than behavioral intention predicted continued platform use, further corroborating the pattern that mandatory adoption disrupts the standard motivational–behavioral sequence. Zheng et al.'s (2025) meta-analytic evidence provides complementary context: across 91 COVID-period e-learning studies, motivational predictors showed stronger effects on intention under mandatory than voluntary conditions, consistent with the interpretation that motivation toward a mandated technology is attitudinally active, shaping how students feel about the system, even when it fails to differentiate behavioral frequency.

The unusually low R^2 for actual use (3.5%) directly reflects this theoretical claim. The motivational predictors in the model account collectively for only a small fraction of variation in how frequently and for how long students use their institution's OLE. Under mandatory conditions, almost all students use the system; the residual variance in frequency and duration is

primarily captured by facilitating conditions (access differentials) rather than by motivational states, leaving the model with limited behavioral explanatory power by design. This is not a statistical shortcoming but a theoretically expected result, which the present study documents in a large Turkish university sample using the complete UTAUT structural model.

Several alternative explanations for the BI→USE null merit consideration. First, actual use was operationalized through self-reported behavioral frequency, which may introduce recall bias and attenuate criterion reliability, downwardly biasing the intention–use coefficient. Second, the cross-sectional design cannot rule out a temporal mismatch: intentions and use behavior were measured simultaneously, but intentions may reflect anticipated future use while the use measure captures recent past behavior, introducing construct-temporal divergence. Third, the actual-use composite captures quantity of use but not quality of engagement; a student who interacts with the OLE minimally but purposefully might score identically on the behavioral criterion to one who is logged in passively for extended periods. Future research incorporating objective log-file data alongside attitudinal measures would sharpen construct validity and provide a more sensitive behavioral criterion.

Taken together, these findings indicate that mandatory use does not merely describe the study's setting; it reshapes the internal structure of the UTAUT model. Under compulsion, the attitudinal predictors (performance expectancy, effort expectancy, and social influence) remain active on the intention side, continuing to shape how students evaluate the system even when its use is required. Their behavioral influence, however, is muted: because mandated use removes the discretion through which intention ordinarily operates, differential use is governed less by motivation than by facilitating conditions, which capture the material capacity to comply. Mandatory use thus relocates the model's explanatory weight from motivational to structural determinants of behavior, extending the UTAUT literature beyond the observation that voluntariness moderates the intention, use path toward specifying how a compulsory context redistributes predictive power across the model's constructs.

6. Practical Implications

The pattern of findings across all five paths carries differentiated implications for distinct educational stakeholders.

For institutional administrators, the sole significant predictor of actual use being facilitating conditions rather than motivational attitudes carries an unambiguous message: differential use in mandatory e-learning contexts is an equity problem before it is a motivation problem. Students with inadequate device access, unreliable internet connectivity, or limited technical support use their institution’s OLE less, not because they are less motivated but because material conditions constrain their capacity. Institutions should conduct equity audits of device access and connectivity before implementing motivation-oriented adoption campaigns, and should prioritize technical helpdesk scalability during high-demand instructional periods. This recommendation is grounded in consistent empirical evidence that infrastructure barriers are the primary discriminators between successful and unsuccessful OLE adoption under mandatory conditions (Almaiah et al., 2020; Ciftci et al., 2023).

For instructional designers, the dominant contribution of performance expectancy indicates that perceived academic utility is the primary attitudinal driver of OLE engagement. OLE interfaces and course structures should make the connection between system features and academic outcomes transparent and legible: submission portals, grade feedback mechanisms, and collaborative tools should be foregrounded, and their contribution to student achievement communicated explicitly. Systems that feel administratively oriented (used primarily for document distribution) are likely to generate lower performance expectancy and, by extension, lower motivational engagement, consistent with the established finding that performance expectancy is the most robust predictor of behavioral intention across UTAUT-based higher education studies (Xue et al., 2024).

For instructors, the significant social influence path indicates that pedagogical use of OLE tools is not motivationally neutral. Instructors who integrate OLEs visibly into formative feedback, synchronous interaction, and active learning structures, rather than using the system primarily for passive content delivery, strengthen students' perception that OLE engagement is valued by those whose judgments matter to them, and thereby support higher behavioral intention, consistent with the theoretical and empirical role of social influence in institutional technology adoption contexts (Venkatesh et al., 2003; Williams et al., 2015).

7. Limitations and Future Directions

Several limitations should inform interpretation of the present findings and guide future research. The cross-sectional design precludes causal inference. Path coefficients represent predictive associations under the specified structural model rather than established causal effects, and the temporal ordering of predictors and criteria cannot be verified in a simultaneous assessment. The non-significant BI→USE path may partly reflect a temporal mismatch between prospective intention and concurrent behavioral report rather than an absence of structural influence. Moreover, because all study variables were collected from the same respondents in a single survey administration, the findings are exposed to common method variance (Podsakoff et al., 2003, 2012), which may have inflated correlations among the attitudinally measured constructs and contributed to the unusually high R^2(BI) = 67.5%. The procedural remedies employed during data collection partially mitigate this concern, but they cannot eliminate it. Longitudinal designs that separate measurement occasions for attitudinal predictors and behavioral criteria, together with marker variable approaches (Podsakoff et al., 2003, 2012) and objective log-data, would permit stronger causal conclusions and reduce method bias.

The sample was drawn from a single Turkish state university, and the same sample was used for both scale development and structural testing, so the psychometric properties reported here await confirmation in independent samples. Generalizability to other institutional contexts, regional systems, and student populations cannot be assumed. The predominantly female composition (74.9% women) is consistent with the institution's enrollment profile but may limit generalizability to contexts with more balanced gender distributions; gender moderates UTAUT path coefficients (Venkatesh et al., 2003), and studies with different gender compositions may yield different relative contributions for effort expectancy and social influence. Single-institution sampling also limits the range of facilitating conditions variability; a multi-institution study would provide more reliable estimates of FC effects and permit institutional-level moderation analyses. Measurement invariance analyses across demographic groups (e.g., gender, year of study, or device access) would further establish whether the instrument functions equivalently across student subpopulations.

Actual use was operationalized as a composite of three ordinal self-report items capturing usage frequency, hours, and minutes. Self-reports of behavioral frequency are subject to recall bias and may not accurately capture the distribution of usage, particularly at the extremes; studies that validate self-reported use against system-generated records should be a methodological priority in future OLE acceptance research. Following item removal, the facilitating conditions and behavioral intention factors were each operationalized with three indicators, the minimum required for local identification. While all loadings were strong and the factors demonstrated adequate reliability and validity, three-indicator factors are just-identified and offer limited overdetermination; future revisions of the instrument should consider developing additional indicators for these two constructs. Finally, although discriminant validity was supported by the HTMT criterion, the heterotrait–monotrait ratio between performance expectancy and behavioral intention (.828) approached the conservative .85 threshold, reflecting the strong theoretical and empirical association between perceived usefulness and intention that is characteristic of UTAUT applications. Researchers applying this instrument should remain attentive to the proximity of these two constructs.

The mandatory character of the online learning context derived from the course structure itself: the sampled students were enrolled in courses offered exclusively online, without a face-to-face alternative. Although this design establishes compulsory use at the course level, the study did not capture students' subjective sense of choice. Because the present study was conducted entirely within a mandatory-use context, its findings should not be generalized to voluntary-use settings. Future research should operationalize voluntariness explicitly (through institutional policy records or direct student reports of perceived choice) and compare voluntary and mandatory adoption contexts through multi-group SEM or interaction-based moderation analyses, enabling the voluntariness moderation proposed by UTAUT to be tested empirically rather than interpreted theoretically.

8. Conclusion

This study makes three contributions to the educational technology literature, centered on understanding technology acceptance under mandatory-use conditions. Its primary contribution is to advance empirical understanding of UTAUT under compulsory online learning by demonstrating that the behavioral intention–actual use path is attenuated to non-significance when institutional mandates override individual choice, and that facilitating conditions become the sole significant predictor of actual use, pointing to infrastructure equity rather than motivational intervention as the most consequential institutional target. Supporting this central contribution, the study provides a context-specific, psychometrically evaluated instrument for assessing Online Learning Environments acceptance and use among Turkish university students, addressing the instrument mismatch documented in prior UTAUT-based e-learning research and offering an empirically grounded basis for cross-cultural adaptation.

While broadly confirming the core determinants of behavioral intention, the findings illuminate a critical boundary condition for the application of UTAUT in educational contexts: the model's motivational chain from intention to behavior requires voluntary discretion to operate as theorized. Under institutional compulsion, the model's architecture predicts motivational orientation rather than behavioral frequency, and structural access, not attitude, determines who uses the system and how much. This qualification has practical consequences for how UTAUT-based research is designed, interpreted, and translated into institutional policy in higher education settings where mandated online learning has become a structural feature rather than an exceptional response.

Data availability: The data are available from the corresponding author upon reasonable request.

Declaration of interest: The author declares no conflicts of interest.

Ethical approval and consent to participate: This study received ethical approval from the Ethics Committee for Social Sciences and Humanities at Bursa Uludağ University (Decision No: 28, Date: 22.05.2026), in accordance with the principles outlined in the Declaration of Helsinki. Also, informed consent was obtained from all subjects involved in the study.

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Appendix 1. Online Learning Environments Acceptance and Use Scale

1. Online learning environments are useful in my learning process.
2. Online learning environments improve my learning performance.
3. Online learning environments speed up my learning process.
4. Online learning environments enrich the learning environment.
5. Online learning environments are compatible with my learning styles.
6. Online learning environments are simple to use and easy to understand.
7. Learning to use online learning environments proficiently is easy for me.
8. It is easy for me to use online learning environments to do what I want to do.
9. I find online learning environments easy to use.
10. The administrators at my university support my use of online learning environments.
11. The instructors at my university think that I should use online learning environments.
12. The students at my university think that I should use online learning environments.
13. People whose opinions I value think that I should use online learning environments.
14. I have the knowledge necessary to use online learning environments.
15. I have the resources necessary to learn to use online learning environments.
16. I can access the resources necessary to learn to use online learning environments.
17. I intend to use online learning environments in the future.
18. I would use online learning environments more if they were more accessible.
19. I plan to use online learning environments as much as conditions allow.