[www.ijeedu.com] OPEN ACCESS

International Journal of Environment, Engineering & Education

ISSN 2656-8039 (Online)
Volume 8 • Issue 2 • June 2026

Received: 13 April 2026 | Accepted: 18 May 2026 | Published: 1 June 2026

Research Article

Service Quality and Perceived Platform Error Exposure in Digital Learning Platforms: An Extended SEM Study of Perceived Value and Continuance Intentions in Indonesia and Malaysia

Zhuofan Chen [a] • Sin Yin Teh [b] • Theam Foo Ng [a,*]

[a] Centre for Global Sustainability Studies, Universiti Sains Malaysia, Penang, Malaysia | [b] School of Management, Universiti Sains Malaysia, Penang, Malaysia

ABSTRACT

Digital learning platforms have become essential academic service systems in higher education, yet e-learning continuance research has largely emphasized positive quality attributes while under examining recurring technical disruptions. This study investigates how service quality and perceived platform error exposure influence perceived value and behavioral intentions among university students in Indonesia and Malaysia. Drawing on the Information Systems Success Model, SERVQUAL, and post-adoption continuance theory, an extended structural equation modelling framework was tested using cross-sectional survey data from 123 undergraduate students, comprising 62 respondents from Indonesia and 61 from Malaysia. The sample included LMS users (69.9%) and MOOC users (30.1%). Data were analyzed using confirmatory factor analysis and SEM in IBM AMOS. The measurement model showed good fit: $\chi^2/df = 1.74$, CFI = 0.961, TLI = 0.954, RMSEA = 0.048, and SRMR = 0.042. In the extended model, service quality positively predicted perceived value ($\beta = 0.593$, $p < 0.001$) and behavioral intentions ($\beta = 0.481$, $p < 0.001$), while perceived value positively predicted behavioral intentions ($\beta = 0.391$, $p < 0.001$). Perceived platform error exposure negatively predicted perceived value ($\beta = -0.314$, $p < 0.001$), and perceived value significantly mediated the service quality–behavioral intention relationship ($\beta = 0.232$, $p < 0.001$). The extended model explained 59.8% of the variance in perceived value and improved model fit relative to the baseline model. These findings position platform error exposure as a distinct negative user-experience construct and highlight the need to improve service quality while reducing recurring technical failures.

KEYWORDS behavioral intentions • digital inclusion • e-learning adoption • information systems success • post-adoption evaluation • user-experience • sustainable higher education

ARTICLE CITATION

Z. Chen, Sin Y. Teh, Theam F. Ng, "Service Quality and Perceived Platform Error Exposure in Digital Learning Platforms: An Extended SEM Study of Perceived Value and Continuance Intentions in Indonesia and Malaysia," International Journal of Environment, Engineering and Education, Vol. 8, No. 2, pp. 243-263, 2026. https://doi.org/10.55151/ijeedu.v8i2.490

*CORRESPONDENCE

Theam Foo Ng tfng@usm.my Centre for Global Sustainability Studies (CGSS), Universiti Sains Malaysia (USM), Level 5, Hamzah Sendut Library, Minden 11800, Penang, Malaysia https://orcid.org/0000-0002-9529-4456

1. INTRODUCTION

Digital learning platforms have become core infrastructure in higher education for content delivery, assignment management, assessment, communication, and blended or online learning. The expansion of LMS, MOOC, and web-based learning environments reflects a shift from supplementary instructional tools to integrated academic service systems. Blended learning can transform how students access content, engage in learning activities, and participate in academic communities. In contrast, post-pandemic online learning has increased the need to distinguish temporary digital delivery from well-designed online learning environments [1]–[3]. Accordingly, digital learning platforms should be understood not only as technological systems, but also as multi-dimensional service environments in which students evaluate system quality, content quality, service support, learner experience, instructor interaction, and learning effectiveness [4]–[8].

The Information Systems Success Model provides a strong theoretical basis for explaining students' evaluation of digital learning platforms. The model argues that system quality, information quality, and service quality influence user satisfaction, intention to use, and perceived benefits [9]–[11]. In e-learning research, these dimensions have been consistently linked to perceived usefulness, satisfaction, learning outcomes, and continuance intention [12], [13]. Prior studies also show that e-learning success depends not only on the availability of digital platforms but also on the extent to which they provide reliable access, useful learning resources, responsive support, usable interfaces, and meaningful learning experiences [14], [15].

Service quality is particularly important because students interact with digital learning platforms as users of educational services. The SERVQUAL tradition conceptualizes service quality in terms of reliability, responsiveness, assurance, empathy, and tangibility, which are relevant to platform stability, support responsiveness, user trust, learner-oriented services, and interface accessibility [16]–[19]. In digital learning contexts, students are more likely to evaluate a platform positively when it enables consistent access to materials, smooth assignment submission, timely technical support, clear navigation, and efficient completion of academic tasks. Previous studies have demonstrated that service quality, system quality, learner support, instructor quality, usability, and information quality affect satisfaction, perceived usefulness, and continued use of e-learning systems [20]–[22].

However, students' behavioral intentions are not shaped solely by quality perceptions. In post-adoption technology use, perceived value plays a central evaluative role because users assess whether the benefits of using a platform justify the time, effort, and inconvenience involved [23]–[25]. Expectation-confirmation theory further explains that users' future intentions are influenced by post-use evaluations of usefulness, confirmation, and satisfaction [26]–[28]. In e-learning, students are more likely to continue using, recommend, or prefer a platform when they perceive it as useful, efficient, supportive, and worth the effort [29], [30]. Thus, perceived value serves as a key mechanism linking platform experience to behavioral intentions.

Despite the extensive literature on service quality, perceived usefulness, satisfaction, and continuance intention, existing e-learning research remains strongly oriented toward positive quality attributes. Less attention has been given to recurring technical disruptions as a distinct negative user-experience construct. In practice, students may perceive a platform as useful, accessible, and supportive while still encountering repeated problems such as buffering, slow loading, freezing, crashes, broken links, delayed access, and failed submissions. These disruptions can occur during critical learning moments, including assignment submission, assessment access, online participation, and material retrieval. Treating such problems merely as low service quality or low system quality may obscure their specific negative impact on perceived value.

This study, therefore, introduces perceived platform error exposure as a distinct negative user-experience construct. Perceived platform error exposure refers to students' subjective perception of recurring technical disruptions encountered during digital learning activities. This construct is conceptually related to system quality and service quality, but it is not identical to them. System quality reflects broader technical performance, usability, functionality, and dependability, while service quality reflects users' evaluation of support, responsiveness, assurance, empathy, and service delivery [9], [31]. By contrast, perceived platform error exposure focuses specifically on repeated error-related experiences that may reduce efficiency, increase frustration, weaken satisfaction, and lower perceived value. Research on technostress and technology-related strain supports this logic by showing that technology problems can increase user strain and reduce system-use satisfaction [32]–[35].

The issue is particularly relevant in Indonesia and Malaysia, where higher education institutions have increasingly adopted LMS, MOOC, and blended-learning platforms. In these contexts, students use digital platforms to access learning materials, communicate with lecturers, submit assignments, participate in online learning activities, and monitor assessment information. However, platform evaluation may depend not only on positive service-quality attributes but also on students' perceived exposure to recurring technical disruptions. Comparative evidence from Indonesia and Malaysia remains limited, especially regarding how service quality and negative platform-error exposure jointly shape perceived value and behavioral intentions. This creates an opportunity to extend e-learning continuance research by examining both positive and negative dimensions of students' platform experience.

Specifically, this study aims to examine students' evaluations of digital learning platforms by integrating positive service-quality perceptions and negative error-related platform experiences within a structural equation modeling framework. The study has three objectives: first, to investigate the direct and indirect relationships among service quality (SQ), perceived value (PV), and behavioral intentions (BI); second, to assess the association between perceived platform error exposure (FERR) and perceived value; and third, to compare the extended model including FERR (M2) with the baseline model excluding FERR (M1) in terms of model fit and structural parameter estimates.

The empirical context comprises undergraduate students from universities in Indonesia and Malaysia. These countries provide a relevant setting because higher education institutions in Southeast Asia have increasingly adopted LMS, MOOC, and blended-learning platforms. Students rely on these platforms to access materials, submit assignments, communicate with lecturers, participate in online activities, and monitor academic information. Thus, their evaluations are shaped not only by service-quality attributes such as reliability, responsiveness, and accessibility, but also by recurring technical disruptions, including buffering, slow loading, crashes, broken links, and failed submissions.

Three research questions guide this study. RQ1: How are service quality and perceived platform error exposure associated with perceived value and behavioral intentions? RQ2: Does perceived value mediate the relationship between service quality and behavioral intentions? RQ3: How does the inclusion of perceived platform error exposure affect the structural estimates and explanatory performance of the SEM model compared with the baseline model?

This study contributes to the literature by positioning FERR as an independent negative user-experience construct distinct from service-quality evaluation, demonstrating its added explanatory value through comparison of baseline and extended SEM models, and offering practical guidance for universities and platform managers to address recurring technical disruptions alongside service quality and usability.

2. LITERATURE REVIEW

2.1. Digital Learning Platforms as Information-System Service Environments

Digital learning platforms have become core infrastructures in higher education, supporting content delivery, assignment management, assessment, communication, and blended or online learning. Beyond serving as repositories of learning materials, these platforms operate as information-system service environments in which students evaluate technical performance, service quality, and learning value. The DeLone and McLean Information Systems Success Model explains that system quality, information quality, and service quality shape user satisfaction, intention to use, and perceived benefits [9], [11], [36]. In e-learning research, these dimensions have been consistently associated with perceived usefulness, satisfaction, learning experience, and continuance intention [20], [21], [37], [38].

From a service-quality perspective, students assess digital learning platforms through reliability, responsiveness, assurance, empathy, and tangibility, as reflected in the SERVQUAL framework [39]. Prior studies show that service quality, system quality, learner support, instructor quality, usability, and information quality influence satisfaction and continued use of e-learning systems [15], [40], [41]. Thus, platform quality should be conceptualized not only as technical functionality but also as educational service support.

Existing studies on e-learning platforms generally emphasize positive quality attributes, such as system quality, service quality, perceived usefulness, satisfaction, and continuance intention [42]–[44]. However, limited attention has been given to recurring technical disruptions, including buffering, slow loading, broken links, crashes, freezing, and failed submissions. This gap is important because students may still perceive a platform as useful while repeatedly encountering errors during critical learning activities. Such disruptions can trigger frustration, technostress, dissatisfaction, and reduced continuance intention [45]–[47]. Therefore, this study treats perceived platform error exposure as a distinct negative user-experience dimension, separate from general service-quality evaluation.

2.2. Service Quality in Digital Learning

Service quality refers to students' evaluation of a digital learning platform's reliability, responsiveness, trustworthiness, learner support, and interface quality. In this study, service quality is grounded in the Information Systems Success Model and operationalized through the SERVQUAL dimensions of reliability, responsiveness, assurance, empathy, and tangibility [9], [17]. This framing is appropriate because digital learning platforms function simultaneously as technical systems and educational service channels through which students access resources, interact with learning activities, and complete academic tasks.

Recent e-learning research suggests that multiple quality dimensions, including service reliability, system performance, information accuracy, usability, learner support, and instructor support, shape students' evaluations of digital learning platforms. These dimensions are not only associated with user satisfaction but also influence perceived usefulness, learning experience, and students' willingness to continue using e-learning systems [43], [48], [49]. Thus, platform quality should be understood as a multi-dimensional construct that connects technical performance, pedagogical support, and students' post-use behavioral responses. These findings indicate that students are more likely to continue using digital platforms when they perceive them as useful, reliable, accessible, and supportive [50]–[52].

Nevertheless, service quality should not be treated as a catch-all construct for platform experience. Students may rate a platform positively for its interface, resources, and support while still experiencing recurring technical issues such as slow loading, buffering, crashes, broken links, or failed submissions. Treating these disruptions merely as low service quality may obscure their distinct negative effect on perceived value and continuance-related evaluations. Therefore, this study distinguishes positive service-quality perceptions from negative error-related platform experiences, particularly because technology-related problems can create strain, reduce satisfaction, and weaken digital service evaluations [53].

2.3. Perceived Value in Digital Learning Continuance

Perceived value is a key factor in students' continuance intention toward digital learning platforms because it reflects their assessment of whether the benefits outweigh the time, effort, and possible inconvenience involved. In digital learning, perceived value emerges when students believe that a platform improves learning efficiency, provides easy access to materials, supports communication, and helps them complete academic tasks effectively [23], [24], [54].

Recent studies show that perceived value is strongly linked to perceived usefulness, satisfaction, confirmation, system quality, service quality, learning support, and continuance intention. Students are more likely to keep using digital learning platforms when they perceive them as reliable, easy to use, pedagogically relevant, and supported by adequate institutional services. Prior research also confirms that e-learning service quality, educational support, course quality, and platform features influence satisfaction, perceived value, and continued use [55]–[59].

Expectation-confirmation theory explains that continued use is shaped by users' post-use evaluation, particularly confirmation, perceived usefulness, and satisfaction [26], [28]. This is relevant in higher education because students may initially use digital platforms due to institutional requirements. However, their continued use depends on whether they perceive them as beneficial and worth continuing. Thus, perceived value acts as an evaluative bridge between digital learning experience, system and service quality, satisfaction, and continuance-related behavior [60], [61].

2.4. Behavioral Intentions in Digital Learning

Behavioral intentions refer to students' willingness to continue using, reuse, recommend, or choose a digital learning platform for future academic activities. In service-quality research, behavioral intentions are important post-consumption outcomes because they reflect users' likelihood of remaining with a service, recommending it, or avoiding alternatives [39]. In digital learning, this construct is especially relevant because universities invest in learning management systems and online platforms with the expectation that students will use them consistently and meaningfully, beyond minimum course requirements.

Prior studies show that behavioral intentions in e-learning are shaped by perceived usefulness, satisfaction, service quality, system quality, confirmation, perceived value, and learning support [62]–[65]. These findings suggest that a single factor does not determine students' intention to continue using digital platforms; rather, it is the accumulated evaluations of system performance, ease of use, academic usefulness, service responsiveness, and overall value. Students who perceive a platform as reliable, useful, efficient, and supportive are therefore more likely to continue using it, recommend it to peers, and choose it when available in future learning contexts [29], [66], [67].

However, behavioral intentions in higher education should be interpreted with care, as platform use is often semi-mandatory. Students may continue using an LMS even when their experience is not fully positive, as required by lecturers or institutions. Therefore, behavioral intentions should be understood more broadly than mere continued use; they should include reuse, recommendations, preferences, and a willingness to choose the platform when alternatives exist. This broader view better captures students' evaluative commitment and distinguishes genuine continuance intention from compliance-based use [30], [68], [69].

2.5. Technical Disruptions and Perceived Platform Error Exposure

Although service quality and perceived value are widely discussed in e-learning studies, students' repeated exposure to platform errors remains less clearly conceptualized as a distinct negative user-experience construct. Perceived platform error exposure refers to students' subjective experience of recurring technical disruptions, such as crashes, freezing, buffering, slow loading, broken links, failed submissions, delayed access, and task-completion errors. These disruptions may occur during critical learning activities and reduce perceived usefulness, efficiency, satisfaction, and overall platform value [13], [20], [40].

Conceptually, this construct is related to but distinct from system quality, service quality, perceived risk, technostress, and objective system failure. System quality reflects overall technical performance and reliability, while service quality concerns support and service delivery [9], [70]. Unlike these broader constructs, perceived platform error exposure specifically captures repeated user encounters with technical errors. It also differs from perceived risk, which concerns anticipated negative consequences, and technostress, which reflects psychological strain from technology use [71], [72].

The distinction between service quality and perceived platform error exposure is theoretically important because positive and negative platform experiences can co-occur. Students may view a platform as useful, organized, and academically supportive, yet still encounter slow loading, failed submissions, crashes, or unstable access during learning tasks. Treating these disruptions merely as low service or system quality may obscure their specific negative effect on perceived value. Therefore, this study conceptualizes perceived platform error exposure as an independent negative user-experience construct to explain better students' evaluations of digital learning platforms beyond conventional quality-based assessments [9], [11], [32].

Table 1. Research Gap and Positioning of the Study

Research area	Established knowledge	Literature gap	Positioning of this study	Sources
The IS Success Model in e-learning	E-learning success is shaped by system quality, information quality, service quality, satisfaction, perceived usefulness, and continuance intention.	Prior studies often treat technical problems as part of broad system or service quality constructs.	This study separates positive service-quality evaluation from perceived platform error exposure.	Al-Fraihat et al., [20]; DeLone & McLean, [9]; Sabeh et al., [73].
Service quality	Service quality influences satisfaction, perceived usefulness, learning outcomes, and continued use in digital learning platforms.	Service quality is often treated as a catch-all construct, focusing on negative technical experiences.	This study conceptualizes service quality as a positive multi-dimensional construct distinct from error exposure.	Cidral et al., [13]; Parasuraman et al., [17]; Udo et al., [74].
Perceived value & continuance	Perceived value, usefulness, confirmation, and satisfaction explain post-adoption continuance in e-learning systems.	Perceived value is often secondary to satisfaction or continuance intention, even though it plays a role in evaluating whether platform use is worthwhile.	This study positions perceived value as the evaluative mechanism linking platform experience to behavioral responses.	Bhattacherjee, [28]; Chiu et al., [29]; Lee, [75].
Technical disruption & negative user experience	Technology-related problems can strain resources, reduce satisfaction, and weaken system use outcomes.	Students' recurring exposure to platform errors is rarely modeled as a distinct construct in digital learning research.	This study introduces perceived platform error exposure as a separate negative user-experience construct.	Ayyagari et al., [32]; Ragu-Nathan et al., [76]; Tarafdar et al., [53].
Contextual evidence	Digital learning platforms are widely used across higher education, including LMS, MOOC, and blended-learning environments.	Evidence from Indonesia and Malaysia remains limited, especially on how service quality and technical errors jointly shape perceived value and behavioral intentions.	This study provides evidence from students in Indonesia and Malaysia to explain digital learning platform evaluation.	Al-Fraihat et al., [20]; Cidral et al., [13].

2.6. Conceptual Framework

This study develops an extended service quality–perceived value–behavioral intention framework to explain students' evaluations of digital learning platforms. The framework integrates the Information Systems Success Model, the SERVQUAL tradition, and post-adoption continuance theory.

Service quality is conceptualized as a multi-dimensional construct reflecting students' evaluation of platform reliability, responsiveness, assurance, empathy, and tangibility. At the same time, perceived value represents students' judgment that the platform provides learning benefits that justify the time and effort required for use [9], [17]. Behavioral intentions capture students' willingness to continue using, reusing, recommending, or choosing the platform in future learning activities [28], [39].

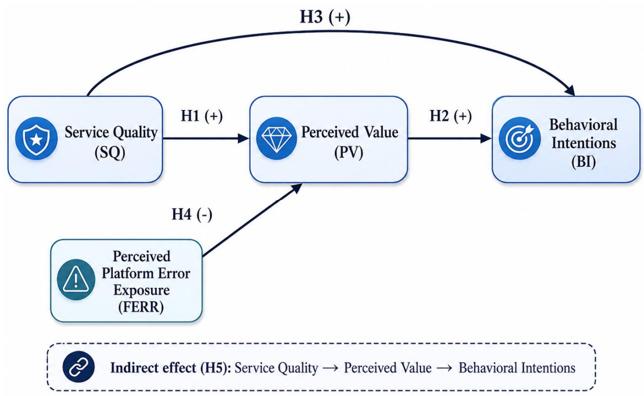

Figure 1. Proposed Conceptual Framework

The framework extends the conventional service quality–continuance logic by incorporating perceived platform error exposure as a distinct negative user-experience construct. Perceived platform error exposure refers to students' perceived exposure to recurring technical disruptions, such as slow loading, buffering, system crashes, broken links, and failed submissions. This construct is distinct from service quality because positive service evaluations and negative technical-error experiences may coexist within the same platform-use context. Thus, the proposed model assumes that students' behavioral responses are shaped not only by positive service-quality perceptions but also by the extent to which technical disruptions weaken perceived platform value.

2.7. Hypotheses Development

2.7.1. Service Quality and Perceived Value

Service quality is expected to enhance students' perceived value of digital learning platforms because users' evaluations of system benefits are shaped by perceptions of usefulness, dependability, and support adequacy [9], [11], [77]. In digital learning environments, platforms that provide stable access, timely technical support, trustworthy functions, learner-oriented features, and accessible interfaces can reduce learning-related friction and strengthen students' perceptions of usefulness and value. Recent studies further show that service quality, system quality, information quality, and support-related factors are associated with perceived usefulness, satisfaction, perceived value, and continuance-related outcomes in online learning and virtual classroom contexts [57], [78]–[81]. Therefore, students who perceive higher service quality are more likely to judge digital learning platforms as valuable for supporting their academic activities.

H1. Service quality is positively associated with perceived value in digital learning platforms.

2.7.2. Perceived Value and Behavioral Intentions

Perceived value is expected to positively influence students' behavioral intentions. Post-adoption technology research suggests that users' future intentions are shaped by their evaluation of whether continued use provides sufficient benefits relative to the effort, time, and inconvenience involved [28], [54], [82]. In digital learning, students are more likely to continue using, recommend, or choose a platform when they perceive that it improves learning efficiency, facilitates access to resources, supports communication, and helps complete academic tasks. Prior studies on e-learning continuance similarly show that perceived usefulness, satisfaction, perceived value, and confirmation are key predictors of continued use intention [29], [30], [69], [83]. Thus, perceived value is expected to strengthen students' behavioral intentions toward digital learning platforms.

H2. Perceived value is positively associated with behavioral intentions in digital learning platforms.

2.7.3. Service Quality and Behavioral Intentions

Service quality may also be directly associated with behavioral intentions. In service research, behavioral intentions reflect users' willingness to continue using a service, recommend it to others, and maintain a favorable relationship with the provider [39]. In digital learning platforms, high service quality can strengthen students' confidence in the platform and increase their willingness to use it again in future academic activities. Previous e-learning studies indicate that system quality, service quality, instructor support, information quality, and usability contribute to students' satisfaction and continuance intention [13], [20], [84]. Therefore, students who perceive the platform as reliable, responsive, accessible, and supportive are more likely to express favorable behavioral intentions.

H3. Service quality is positively associated with behavioral intentions in digital learning platforms.

2.7.4. Perceived Platform Error Exposure and Perceived Value

Perceived platform error exposure is expected to reduce perceived value. Although a platform may offer useful learning resources and supportive services, recurring technical disruptions can increase students' effort, disrupt learning activities, and reduce confidence in completing tasks. Technical problems such as buffering, crashes, slow loading, broken links, and failed submissions may be especially consequential when they occur during assignment submission, assessment access, or time-sensitive learning tasks. Studies on technostress and information-system use show that technology-related problems can increase strain, reduce satisfaction, and weaken users' evaluations of digital systems [32], [53], [76]. Accordingly, students who experience higher platform error exposure are likely to perceive lower platform value.

H4. Perceived platform error exposure is negatively associated with perceived value in digital learning platforms.

2.7.5. Mediating Role of Perceived Value

Perceived value is proposed as a mediating mechanism between service quality and behavioral intentions. Service quality may not directly translate into continued use or recommendation; rather, students first evaluate whether the platform's reliability, responsiveness, accessibility, and support provide sufficient academic value. This logic is consistent with expectation-confirmation and continuance theory, which suggests that post-use evaluations shape users' future behavioral responses [28], [85]. Prior e-learning studies also indicate that perceived value, satisfaction, and perceived usefulness function as evaluative mechanisms linking platform quality to continuance intention [29], [86]. Therefore, perceived value is expected to explain part of the association between service quality and behavioral intentions.

H5. Perceived value mediates the association between service quality and behavioral intentions in digital learning platforms.

3. MATERIALS AND METHODS

3.1. Study Design

This study used an explanatory cross-sectional survey to examine associations among service quality, perceived value, behavioral intentions, and perceived platform error exposure in students' use of digital learning platforms. Grounded in a post-positivist correlational approach, the study tested theory-based relationships among latent constructs without claiming causality. The unit of analysis was the individual university student, and all constructs were measured using self-reported questionnaire items. Methodological reporting followed transparency principles for observational studies and SEM by specifying eligibility criteria, data screening, construct operationalization, measurement, structural model testing, mediation analysis, and model comparison [87], [88].

SEM was appropriate because it simultaneously estimates latent constructs, indicators, and structural paths while accounting for measurement error. It also enabled testing perceived value as a mediator between service quality and behavioral intentions, and comparing the baseline SQ–PV–BI model with an extended model that includes perceived platform error exposure as a distinct negative user-experience construct [89], [90]. Because the study was cross-sectional and non-experimental, all path coefficients were interpreted as statistical associations rather than causal effects.

3.2. Research Context

This study was carried out in higher education settings in Indonesia and Malaysia. Both countries have increasingly adopted learning management systems, blended learning, MOOC platforms, and other forms of post-pandemic digital learning. In these environments, students use digital platforms to access course materials, communicate with lecturers and peers, submit assignments, join online activities, and check assessment information. This makes the context appropriate for studying both students' positive evaluations of platform services and their negative experiences with technical problems.

The study viewed digital learning platforms as service systems rather than merely technical tools. Therefore, the analysis focused on students' perceived experiences rather than objective server performance. Perceived platform error exposure was measured from students' reports of recurring issues such as buffering, slow loading, system crashes, broken links, and submission errors, rather than from platform log data.

3.3. Population, Eligibility Criteria, and Participants

The target population was university students in Indonesia and Malaysia who had used a digital learning platform during the current or previous academic term. The study used purposive sampling because participants needed direct experience with LMS or MOOC platforms to assess service quality, perceived value, behavioral intentions, and technical disruptions.

Participants were eligible if they were currently enrolled university students, had recently used an LMS or MOOC platform, and had enough experience to evaluate both platform services and technical problems. Responses were excluded when participants failed to meet these criteria, submitted unusable incomplete data, failed attention checks, or were detected as multivariate outliers.

After data screening, the final respondents were from Indonesia and Malaysia. The sample represented LMS and MOOC users, STEM and non-STEM students, and students from public, private, and technical universities. Because the total number of survey invitations was not recorded, the response rate could not be calculated.

3.4. Sample Size

The sample size was assessed by considering whether it was sufficient for the scope and complexity of the proposed SEM model. The final analysis used data from 123 respondents. Although this number is relatively modest for a covariance-based SEM, it was considered acceptable for an exploratory theory-testing study because the model was not overly complex. It consisted of four key latent constructs, one mediation pathway, and a second-order service quality construct.

Several considerations supported the adequacy of the sample. These included the parsimonious structure of the model, the quality of the measurement model, the successful convergence of both the CFA and SEM analyses, acceptable overall model fit, and the consistency of standardized estimates and confidence intervals. This evaluation follows common SEM reporting guidance, which recommends assessing sample size alongside model complexity, factor loading strength, estimation approach, and overall model performance, rather than relying only on a fixed minimum sample-size rule [91], [92].

3.5. Instrument Development and Content Validation

The questionnaire was developed by adapting established scales and applying a systems-engineering-informed item-development process. Constructs were drawn from information systems, service quality, continuance, and behavioral intention literature. Service Quality was based on the DeLone and McLean IS success model and measured through SERVQUAL dimensions—reliability, responsiveness, assurance, empathy, and tangibility [9], [17]. Its second-order specification is consistent with recent studies on e-learning and MOOC service quality [73], [93]. Perceived Value was adapted from expectation-confirmation and IS continuance research [94], while Behavioral Intentions followed service-quality behavioral intention literature [39].

The FERR construct was developed to measure students' perceived exposure to recurring platform errors, following scale development principles involving construct definition, domain specification, stakeholder input, expert review, and pilot testing [95], [96]. Input from 20 stakeholders—12 learners, 5 teachers, and 3 IT administrators—yielded 42 user needs, including buffering, slow loading, failed submissions, delayed grade display, broken links, crashes, and poor responsiveness to support requests. These needs were translated into formal requirements and perception-based survey items. At the same time, technical indicators such as page-load time, submission success rate, broken-link frequency, and crash frequency served only as design references, not objective log data. Expert review and a pilot test with 25 students resulted in minor wording revisions, with no items deleted and reliability above 0.87 for all constructs.

3.6. Operationalization and Measurement

All constructs were measured with seven-point Likert scales ranging from 1 = strongly disagree to 7 = strongly agree. Higher scores for SQ, PV, and BI reflected more positive evaluations of service quality, perceived value, and behavioral intentions. In comparison, higher FERR scores indicated greater perceived exposure to recurring technical problems. Composite scores were used only for descriptive purposes; the CFA and SEM analyses treated each construct as a latent variable, estimated from its indicators.

Table 2. Operational definitions, dimensional structure, number of items, and measurement sources for the latent constructs.

Construct	Dimensions	Operational	Source or Development Basis
Service Quality (SQ)	Second-order construct; 16 items across REL, RES, ASS, EMP, TAN	Students' overall evaluation of reliability, responsiveness, assurance, empathy, and tangibility in the digital learning platform.	Adapted from the IS success model and SERVQUAL tradition [9], [17]; supported by e-learning service-quality research [73], [93].
Perceived Value (PV)	5 items	Students' evaluations of the platform's benefits, usefulness, efficiency, and learning support justify the effort required to use it.	Adapted from expectation-confirmation and IS continuance research [94].
Behavioral Intentions (BI)	4 items	Students' intention to continue using, reuse, recommend, or choose the platform when available.	Adapted from behavioral consequences of service quality research [39].
Perceived Platform Error Exposure (FERR)	3 items	Students' perceived exposure to recurring technical disruptions, including freezing, buffering, slow loading, submission errors, broken links, and task-completion problems.	Developed through stakeholder elicitation, traceability, expert review, and pilot testing following scale-development guidance [95], [96].

Service Quality was modeled as a reflective second-order construct comprising reliability, responsiveness, assurance, empathy, and tangibility, reflecting a broad evaluation of related service attributes. While a correlated first-order model may be tested for sensitivity, the second-order specification was retained for parsimony and consistency with the study framework. Perceived Value captured students' judgments of usefulness, efficiency, and learning value, while Behavioral Intentions reflected their likelihood of continued use, recommendation, and future platform choice.

Perceived Platform Error Exposure measured recurring technical issues such as crashes, buffering, slow loading, submission errors, broken links, and task-completion problems, and was treated as a distinct negative user-experience construct rather than a reverse indicator of service quality.

3.7. Survey Administration and Response Quality

Data were collected via an online LimeSurvey questionnaire over four weeks, from February to March 2026. Before participation, respondents received an electronic information sheet and provided informed consent. The survey required responses to displayed items to reduce missingness, although partial completion and early termination resulted in a final item-level missing-data rate of 0.8%. Two attention-check items were included, and respondents who failed them were excluded before analysis. One participant was randomly selected to receive a USD 20 voucher, administered independently from response data.

Procedural safeguards were implemented to reduce social desirability bias and common-method bias. Respondents were informed that participation was voluntary, responses were anonymous, no names or IP addresses were collected, and there were no right or wrong answers. These steps were intended to encourage honest responses and improve data credibility.

3.8. Data Management, Cleaning and Screening

Before CFA and SEM, the dataset was screened for eligibility, completion, attention-check performance, missing data, invalid response patterns, multivariate outliers, distributional properties, multicollinearity, and common method variance. Missing data were handled using Expectation Maximization, while multivariate outliers were identified using Mahalanobis distance at $p < 0.001$ and removed.

Descriptive statistics, including means, standard deviations, skewness, kurtosis, minimums, and maximums, were examined for the main constructs. Multicollinearity was assessed using VIF values; values below 5.0 were considered acceptable. Given the cross-sectional self-report design, common method variance was assessed using Harman's single-factor test, while acknowledging that common method bias cannot be fully ruled out in self-report survey research [97].

3.9. Data Analysis and Measurement Model

CFA and SEM were conducted using IBM SPSS AMOS. Because the questionnaire used a seven-point response scale and showed acceptable distributional properties, the indicators were treated as approximately continuous, which is appropriate for ordinal items with five or more categories when the focus is on latent-variable relationships rather than on categorical threshold interpretation [98]. Maximum likelihood estimation was applied, and model fit was assessed using χ^2/df, CFI, TLI, RMSEA, and SRMR. These indices were interpreted alongside theoretical relevance and parameter estimates rather than as fixed cutoffs [88], [99].

The measurement model was evaluated before testing structural relationships and included 28 indicators and four main latent constructs. Service Quality was specified as a reflective second-order construct formed by reliability, responsiveness, assurance, empathy, and tangibility. At the same time, Perceived Value, Behavioral Intentions, and Perceived Platform Error Exposure were modeled as first-order reflective constructs. Convergent validity was assessed using standardized factor loadings, composite reliability, AVE, and Cronbach's alpha, with thresholds of ≥0.70 for loadings and reliability, and ≥0.50 for AVE [100]. Discriminant validity was tested using HTMT, with values below 0.85 indicating adequate distinction [101]. Mediation effects were examined through bootstrapping with 5,000 resamples, standardized estimates, standard errors, p-values, and 95% confidence intervals.

3.10. Structural Model and Hypothesis Testing

The baseline model (M1) represented the traditional service quality-perceived value-behavioral intentions framework. It specified paths from service quality to perceived value, from perceived value to behavioral intentions, and from service quality to behavioral intentions. The extended model (M2) retained these paths and added perceived platform error exposure as a negative predictor of perceived value. SQ and FERR were allowed to covary because both were exogenous latent constructs in the extended specification.

The indirect association between service quality and behavioral intentions through perceived value was computed as the product of the SQ–PV and PV–BI paths. The total association between SQ and BI was computed as the sum of the direct SQ-BI path and the indirect SQ–PV–BI path. Structural results should be reported using unstandardized estimates, standardized coefficients, robust standard errors, p values, 95% confidence intervals, R-squared values for endogenous constructs, and effect-size estimates where appropriate. Effect size f2 and interpreted cautiously using small, medium, and large conventions as descriptive benchmarks [102].

3.11. Model Comparison Strategy

Model comparison was conducted to assess whether FERR should be specified as an independent negative user-experience construct. The main test used a nested-model procedure with the same observed indicators: the restricted model retained the full measurement structure but fixed the FERR toward the Perceived Value path to zero. In contrast, the extended model freely estimated this path. Because the models differed only by this structural constraint, a formal scaled chi-square difference test under robust estimation was appropriate [103].

A descriptive comparison was also made between the conventional SQ–PV–BI model and the extended model, including FERR and its indicators. Since these models differed in measurement specification, they were not treated as strictly nested; therefore, CFI, TLI, RMSEA, SRMR, AIC, and BIC were used to compare approximate and information-based fit. Lower AIC/BIC, higher CFI/TLI, and lower RMSEA/SRMR indicated better relative performance. For measurement-invariance and group comparisons, changes in CFI and RMSEA were used alongside chi-square results to determine whether added constraints meaningfully worsened model fit [104], [105].

4. RESULTS

4.1. Data Screening and Sample Characteristics

The final analytic sample consisted of 123 university students from Indonesia (n = 62) and Malaysia (n = 61), representing an almost balanced country distribution. Most respondents were LMS users, with the remainder using MOOC platforms, and the sample included both STEM and non-STEM students, providing a relevant basis for examining digital learning platform experiences across academic backgrounds.

Table 3. Demographic and academic characteristics of the final analytic sample.

Category	Items	Frequency (N=123)	Percentage
Country	Indonesia	62	50.40%
	Malaysia	61	49.60%
Gender	Female	66	53.70%
	Male	57	46.30%
Age	18-22 years	78	63.40%
	Other age groups	45	36.60%
Platform type	LMS	86	69.90%
	MOOC	37	30.10%
Discipline	STEM	74	60.20%
	Non-STEM	49	39.80%

Preliminary diagnostics indicated that the retained dataset was suitable for further CFA and SEM analysis. Multicollinearity was not a serious concern because the variance inflation factor values ranged from 1.12 to 2.84, which were below the conservative threshold of 5.0. Because the study used cross-sectional self-reported questionnaire data, common method variance was examined using Harman's single-factor test. The first unrotated factor accounted for 38.4% of the total variance, below the commonly used 50% threshold. This result indicates that common method variance was unlikely to dominate the observed relationships, although it cannot be fully ruled out in self-report survey research.

4.2. Descriptive Statistics

Descriptive statistics were calculated for the four main constructs: Service Quality (SQ), Perceived Value (PV), Behavioral Intentions (BI), and Perceived Platform Error Exposure (FERR). Mean scores for SQ, PV, and BI were above the scale midpoint, indicating generally favorable evaluations of digital learning platforms among respondents. The mean score for Ferr was lower than the midpoint, suggesting that perceived technical disruptions were present but not dominant in the overall sample.

Table 4. Descriptive Statistics of Study (N = 123)

Construct	Mean	SD	Skew.	Kurt.	Min	Max
SQ	4.82	1.14	−0.38	−0.27	1.63	7.00
PV	4.67	1.21	−0.44	−0.19	1.40	7.00
BI	4.91	1.18	−0.51	0.12	1.50	7.00
FERR	3.24	1.47	0.62	−0.41	1.00	6.67

The skewness and kurtosis values were within acceptable descriptive ranges, supporting the use of SEM with robust maximum likelihood estimation. FERR showed positive skewness, indicating that a smaller subset of respondents reported higher perceived error exposure.

4.3. Reliability and Convergent Validity

Reliability and convergent validity were assessed using standardized factor loadings, Composite Reliability (C.R.), Average Variance Extracted (AVE), and Cronbach's alpha. All standardized loadings exceeded 0.70, with the lowest being EMP3 (λ = 0.747). C.R values ranged from 0.861 to 0.932, exceeding the recommended 0.70 threshold. AVE values ranged from 0.609 to 0.774, exceeding the 0.50 criterion. Cronbach's alpha values ranged from 0.857 to 0.930, indicating satisfactory internal consistency.

Table 5. Reliability and convergent validity indicators for the first-order and main latent constructs.

Construct	Loading Range	CR	AVE	Cronbach's α
Reliability (REL)	0.804 – 0.841	0.893	0.677	0.891
Responsiveness (RES)	0.789 – 0.856	0.907	0.662	0.904
Assurance (ASS)	0.818 – 0.868	0.906	0.708	0.903
Empathy (EMP)	0.747 – 0.804	0.861	0.609	0.857
Tangibility (TAN)	0.775 – 0.812	0.871	0.631	0.868
Perceived Value (PV)	0.819 – 0.862	0.924	0.710	0.921
Behavioral Intentions (BI)	0.868 – 0.894	0.932	0.774	0.930
Perceived Platform Error Exposure (FERR)	0.862 – 0.891	0.908	0.766	0.905

Note. Full item Factor Loadings, Composite Reliability, AVE, and Cronbach's Alpha are reported in Supplementary Table S2.

The second-order loadings for SQ were also acceptable, with reliability (λ = 0.874), responsiveness (λ = 0.891), assurance (λ = 0.847), empathy (λ = 0.813), and tangibility (λ = 0.786) all loading substantially on the higher-order SQ construct. These results support the specification of SQ as a multi-dimensional second-order construct.

4.4. Discriminant Validity

Discriminant validity was examined using the Heterotrait–Monotrait ratio (HTMT). All HTMT values were below the conservative 0.85 threshold, indicating that the constructs were empirically distinguishable. The highest HTMT value was observed between PV and BI (0.741), as expected given the close relationship between perceived value and behavioral intention. Importantly, HTMT values between FERR and the five service quality dimensions ranged from 0.329 to 0.438, supporting the distinction between perceived exposure to technical errors and positive service-quality evaluations.

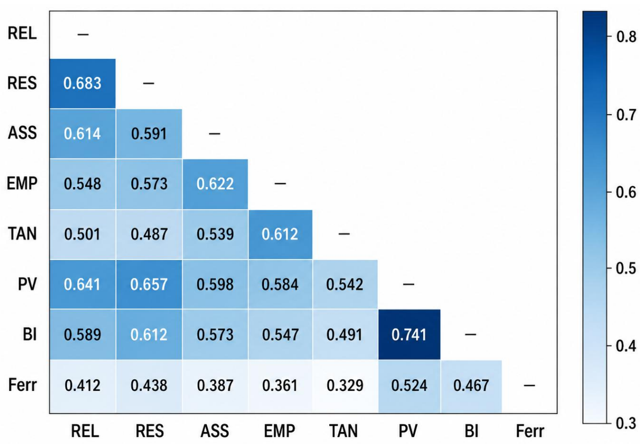

Figure 2. HTMT matrix showing discriminant validity.

4.5. Measurement Model Assessment

Confirmatory factor analysis was conducted to assess the adequacy of the measurement model. The model included 28 observed indicators and four main latent constructs: SQ, PV, BI, and Ferr. SQ was specified as a second-order construct reflected by five first-order dimensions: reliability, responsiveness, assurance, empathy, and tangibility.

The measurement model showed acceptable-to-good fit across the reported indices. The χ^2/df value was below 3.00, CFI and TLI exceeded 0.95, RMSEA was below 0.06, and SRMR was below 0.08. These results indicate that the proposed measurement structure was consistent with the observed data.

Table 6. Confirmatory factor analysis fit indices for the measurement model.

Fit Index	Criterion	Obtained Value	Assessment
χ^2/df	< 3.00	1.74	Acceptable
CFI	≥ 0.95	0.961	Good
TLI	≥ 0.95	0.954	Good
RMSEA	≤ 0.06	0.048	Good
SRMR	≤ 0.08	0.042	Good

4.6. Structural Model Baseline Model M1 and Extended Model M2

Two structural models were estimated to examine the hypothesized relationships. The baseline model (M1) tested the conventional service quality–perceived value–behavioral intentions framework, whereas the extended model (M2) incorporated perceived platform error exposure as an additional negative predictor of perceived value.

Figure 3 presents the baseline model. The model specifies service quality as a second-order construct reflected by reliability, responsiveness, assurance, empathy, and tangibility. As shown in Table 7, all hypothesized paths in M1 were statistically significant. Service quality was strongly associated with perceived value (β = 0.714, $p < 0.001$) and behavioral intentions (β = 0.587, $p < 0.001$), while perceived value was positively associated with behavioral intentions (β = 0.423, $p < 0.001$). The indirect association between service quality and behavioral intentions through perceived value was also significant (β = 0.302, $p < 0.001$).

These results indicate that students' favorable evaluations of platform service quality increase perceived value and future use intentions, partly through perceived value's mediating role. M1 explained 51.0% of the variance in perceived value and 62.4% of the variance in behavioral intentions.

Figure 4 presents the extended model. By adding perceived platform error exposure, M2 captures the negative experiential dimension of digital platform use. As reported in Table 8, service quality remained positively associated with perceived value (β = 0.593, $p < 0.001$, 95% BCa CI [0.472, 0.701]) and behavioral intentions (β = 0.481, $p < 0.001$, 95% BCa CI [0.328, 0.634]). Perceived value also remained a significant predictor of behavioral intentions (β = 0.391, $p < 0.001$, 95% BCa CI [0.255, 0.527]). Importantly, perceived platform error exposure showed a significant negative association with perceived value (β = −0.314, $p < 0.001$, 95% BCa CI [−0.453, −0.175]), indicating that recurring technical disruptions reduce students' evaluation of platform value. The indirect effect of service quality on behavioral intentions through perceived value also remained significant (β = 0.232, $p < 0.001$, 95% BCa CI [0.127, 0.352]). M2 explained 59.8% of the variance in perceived value, suggesting improved explanatory power after incorporating platform error exposure.

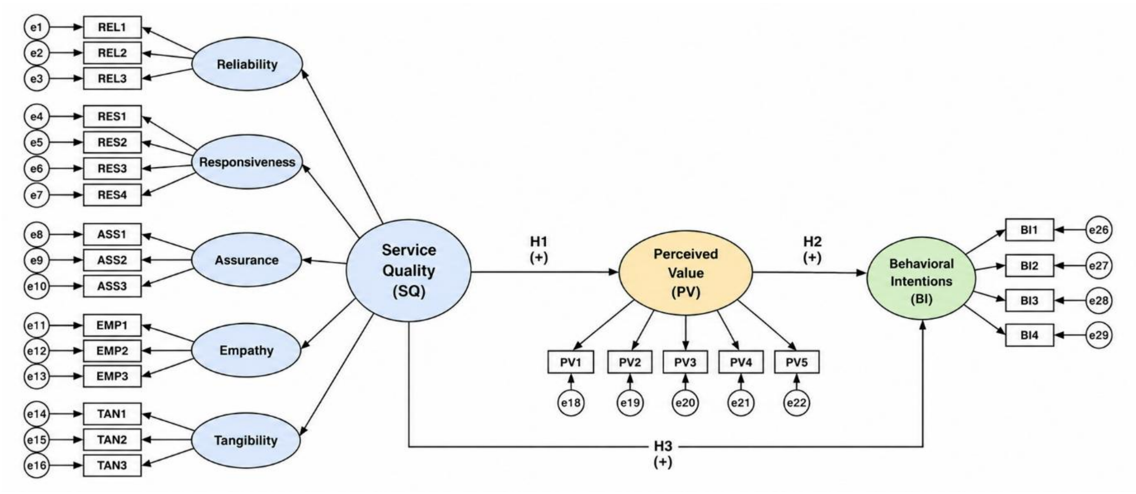

Figure 3. Baseline structural model (M1) excluding perceived platform error exposure.

Table 7. Standardized structural path estimates, significance levels, and explained variance for the baseline model.

Hypothesis	Path	Standardized β	p-value	Interpretation
H1 – M1	SQ → PV	0.714	<0.001	Positive association
H2 – M1	PV → BI	0.423	<0.001	Positive association
H3 – M1	SQ → BI	0.587	<0.001	Positive association
H4 – M1	SQ → PV → BI	0.302	<0.001	Significant indirect association

Note. R^2 values: PV = 0.510; BI = 0.624.

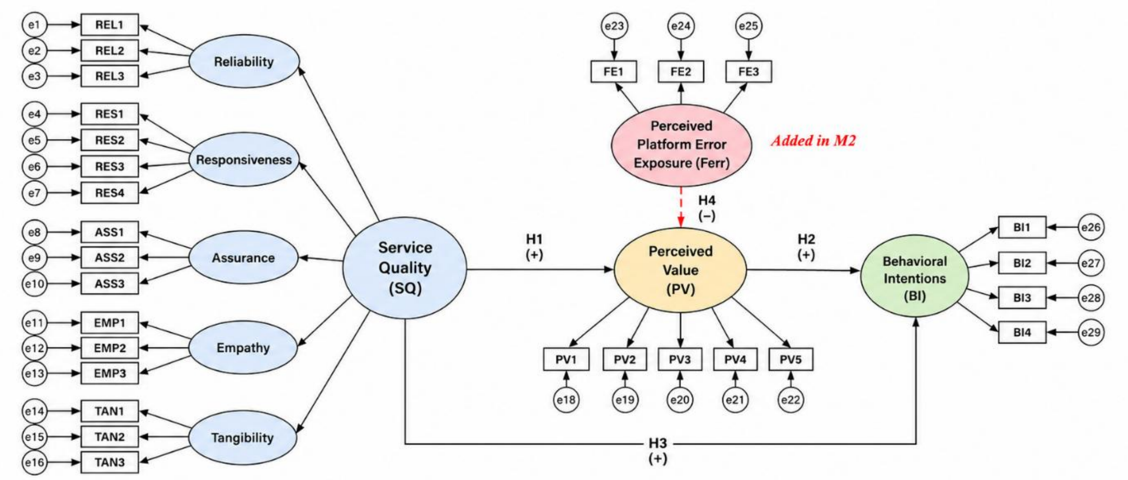

Figure 4. Extended structural model (M2) including perceived platform error exposure as a negative predictor of perceived value.

Table 8. Standardized path estimates, bias-corrected confidence intervals, and effect sizes for the extended SEM model.

Hypothesis	Path	Standardized β	p-value	95% BCa CI	f^2	Interpretation
H1 – M2	SQ → PV	0.593	<0.001	[0.472, 0.701]	0.38	Positive association
H2 – M2	PV → BI	0.391	<0.001	[0.255, 0.527]	0.18	Positive association
H3 – M2	SQ → BI	0.481	<0.001	[0.328, 0.634]	0.22	Positive association
H4 – M2	FERR → PV	−0.314	<0.001	[−0.453, −0.175]	0.12	Negative association
H5 – M2	SQ → PV → BI	0.232	<0.001	[0.127, 0.352]	—	Significant indirect association

Note. R^2 value: PV = 0.598. BCa = bias-corrected and accelerated bootstrap confidence interval.

To further assess the contribution of perceived platform error exposure, the baseline model (M1) and the extended model (M2) were compared on global model fit, information criteria, and changes in structural estimates. Because M2 includes an additional construct and indicators, the comparison is interpreted as a descriptive evaluation of alternative model specifications rather than as a strict nested-model test. Table 9 compares model fit indices between M1 and M2. In contrast, Table 10 presents changes in the standardized direct, indirect, and total associations between service quality and behavioral intentions after perceived platform error exposure was incorporated into the model.

Table 9. Descriptive comparison of baseline and extended model fit based on global fit indices and information criteria.

Fit Index	M1 Baseline Model	M2 Extended Model	Difference
χ^2 scaled	612.38	574.61	−37.77
df	352	349	−3.00
χ^2/df	1.74	1.65	−0.09
CFI	0.952	0.964	+0.012
TLI	0.946	0.958	+0.012
RMSEA	0.053	0.046	−0.007
SRMR	0.051	0.039	−0.012
AIC	8347.12	8289.45	−57.67
BIC	8521.83	8472.94	−48.89

Table 10. Differences in SQ–BI estimates across M1 and M2

Parameter	M1 Estimate	M2 Estimate	Difference Relative to M2
SQ → BI direct	0.587	0.481	22.04%
SQ → PV → BI indirect	0.302	0.232	30.17%
Total SQ → BI	0.889	0.713	24.68%

A model comparison was conducted to evaluate whether including perceived platform error exposure improved the structural specification. As summarized in Table 9, the extended model (M2) consistently provided a better fit than the baseline model (M1). M2 produced a lower χ^2/df value (1.65 vs. 1.74), higher incremental fit indices, including CFI (0.964 vs. 0.952) and TLI (0.958 vs. 0.946), and lower residual-based indices, including RMSEA (0.046 vs. 0.053) and SRMR (0.039 vs. 0.051). The information criteria also favored M2, as indicated by lower AIC and BIC values. Although the two models are best interpreted as alternative specifications rather than strictly nested models due to the additional FERR construct and indicators in M2, the overall pattern suggests that the extended model provides a better representation of the observed data.

Table 10 further indicates that the estimated association between service quality and behavioral intentions became smaller after perceived platform error exposure was incorporated. The direct SQ–BI coefficient decreased from $\beta = 0.587$ in M1 to $\beta = 0.481$ in M2, while the indirect SQ–PV–BI coefficient declined from $\beta = 0.302$ to $\beta = 0.232$. Consequently, the total SQ–BI association decreased from $\beta = 0.889$ to $\beta = 0.713$. This reduction suggests that the magnitude of the service quality effect is sensitive to model specification. Specifically, when recurring platform errors are omitted, the baseline model may attribute a larger share of students' behavioral intentions to service quality. The extended model, therefore, offers a more nuanced explanation by distinguishing positive service-quality perceptions from negative error-related platform experiences.

5. DISCUSSION

This study provides an empirically grounded explanation of students' continuance intention toward digital learning platforms by demonstrating that platform evaluation is shaped by both enabling and disruptive experiences. The baseline model confirmed the conventional pathway in which service quality strengthens perceived value and behavioral intentions, while perceived value further enhances behavioral intentions. The extended model, however, offers a more refined explanation by showing that perceived platform error exposure significantly weakens perceived value and reduces the magnitude of the service quality effect. This finding indicates that students' judgments of digital learning platforms do not emerge solely from positive assessments of service quality, reliability, responsiveness, or institutional support, but also from repeated encounters with technical disruption, such as slow loading, system crashes, failed submissions, buffering, broken links, and delayed access. Thus, the findings support a dual-valence interpretation of digital learning continuance: positive service experiences enhance perceived value, whereas recurring platform errors diminish it.

The positive effect of service quality on perceived value is consistent with the Information Systems Success Model, which positions system quality, information quality, and service quality as core determinants of information-system evaluation, user satisfaction, perceived benefits, and continued use [9], [11]. It also aligns with SERVQUAL theory, which conceptualizes service quality as reliability, responsiveness, assurance, empathy, and tangible service features [17]. In digital learning environments, these dimensions are reflected in platform stability, accessible learning materials, intuitive navigation, timely feedback, responsive technical support, and institutional readiness to assist users. Recent studies similarly show that e-learning continuance is strengthened when platforms are perceived as useful, easy to use, task-compatible, well supported, and aligned with students' academic needs [22], [58], [106]. This means that students do not evaluate digital learning platforms merely as technical systems, but as integrated academic service environments that mediate access to learning, interaction, assessment, and institutional communication.

The significant role of perceived value indicates that students' behavioral intentions depend on whether the platform is perceived as academically useful, efficient, and worth the time and effort required to use it. This finding is consistent with expectation-confirmation theory, which explains that post-adoption intention is shaped by users' evaluation of usefulness, confirmation, and satisfaction after actual system experience [28]. It also supports the perceived value perspective, which defines value as users' overall assessment of benefits relative to costs, effort, risk, and inconvenience [17], [23]. In the context of higher education, perceived value operates as an evaluative mechanism that translates students' experience of service quality into future behavioral responses. When students believe that a platform helps them access academic resources, submit assignments, communicate with lecturers, participate in online learning, and complete coursework efficiently, they are more likely to continue using it, recommend it, or choose it in the future. Recent empirical work on e-learning confirms that satisfaction, perceived usefulness, perceived ease of use, task–technology fit, educational support, emotional support, and perceived value are central mechanisms underlying students' continuance intention [58], [61], [106].

The negative effect of perceived platform error exposure on perceived value is the most theoretically important finding of the extended model. Prior e-learning studies often treat technical problems as part of system quality or service quality. The present study shows that recurring technical disruptions should be conceptualized as a distinct negative user-experience construct rather than merely as the absence of service quality. This distinction is important because a platform may be perceived as useful, institutionally supported, and academically necessary, yet still generate frustration due to repeated technical failures. The discriminant validity results support this interpretation by showing that perceived platform error exposure is empirically distinguishable from service quality. Therefore, positive and negative platform experiences can coexist within the same digital learning environment and should be modeled separately.

This result is consistent with the technostress literature, which shows that technology-related strain can reduce perceived usefulness, satisfaction, learning quality, and continuance intention [32], [46], [53], [107]. In digital learning contexts, technical disruptions are not minor operational inconveniences. They often occur during high-stakes academic moments, including examinations, assignment submission, attendance verification, access to grades, synchronous learning sessions, and retrieval of learning materials. When such disruptions occur repeatedly, students may perceive the platform as unreliable, inefficient, and academically risky. This explains why perceived platform error exposure weakens perceived value even when service quality remains positively associated with behavioral intentions. The finding, therefore, advances digital learning continuance research by demonstrating that negative technical experiences can directly undermine students' value-based evaluation of platform use.

The comparison between the baseline and extended models further strengthens the contribution of this study. By incorporating perceived platform error exposure, the extended model provides a more balanced explanation of students' platform evaluation. The improvement in model fit and the higher explained variance in perceived value indicate that digital learning continuance cannot be adequately explained by positive quality attributes alone. More importantly, the reduction in the direct, indirect, and total effects of service quality after adding perceived platform error exposure suggests that models excluding recurring technical disruptions may overestimate the explanatory power of service quality. In other words, when platform errors are not explicitly modeled, their negative influence may be hidden within broader evaluations of service or system quality. The extended model, therefore, contributes to the information systems and educational technology literature by integrating positive service evaluations and negative disruption exposure within a single continuance framework.

Theoretically, this study extends the Information Systems Success Model by positioning perceived platform error exposure as a distinct negative construct that directly weakens perceived value. This refinement is important because digital learning success is often explained through system quality, information quality, service quality, perceived usefulness, satisfaction, and intention to use. The present findings suggest that this explanation remains incomplete unless recurring technical disruptions are also included as a separate source of value erosion. The study also contributes to expectation-confirmation and perceived value literature by showing that post-adoption evaluation in digital learning is not only driven by perceived usefulness and confirmation, but also by the extent to which the platform avoids repeated technical failures. Empirically, the study extends the evidence base in Southeast Asian higher education by examining students in Indonesia and Malaysia, contexts where LMS, MOOCs, blended learning, and hybrid academic services have become increasingly embedded in university practice.

Practically, the findings suggest that universities and platform providers should adopt a dual improvement strategy. First, they must continue strengthening service quality through reliable access, clear navigation, responsive helpdesk services, stable delivery of learning materials, instructor support, and timely institutional communication. Second, they must treat recurring platform errors as strategic educational risks rather than routine technical problems. Failed submissions, crashes, slow loading, buffering, broken links, and access errors can directly reduce students perceived value and weaken their willingness to continue using the platform. Universities should therefore implement proactive error monitoring, routine platform audits, real-time incident reporting, backup submission channels, server-capacity planning during peak academic periods, and transparent communication when disruptions occur. These interventions are especially important during examinations, assignment deadlines, synchronous sessions, registration periods, and grade-access windows, where technical failures can cause academic anxiety and erode trust in the digital learning system.

This survey has several boundaries. First, its cross-sectional design limits causal interpretation; thus, the SEM results should be viewed as statistical associations. Future studies should use longitudinal, experimental, or mixed-method approaches to examine changes in service quality, platform error exposure, perceived value, satisfaction, and behavioral intentions over time. Second, reliance on self-reported data may not fully capture actual platform performance; therefore, future research should combine survey data with objective platform logs, such as downtime, page-load speed, failed submissions, crash reports, helpdesk tickets, and learning analytics. Third, broader multi-country and multi-platform studies are needed to test the model across institutional types, disciplines, digital competence levels, and platform categories. Future research may also include satisfaction, trust, instructor presence, institutional support, digital competence, self-efficacy, perceived usefulness, and technostress to explain more comprehensively how platform quality and errors shape perceived value and continuance intention.

6. CONCLUSION

This study concludes that service quality and perceived platform error exposure influence students' continuance intentions toward digital learning platforms. Service quality enhances perceived value and behavioral intentions through reliable access, responsive support, clear navigation, and effective academic services. In contrast, recurring technical problems such as slow loading, crashes, broken links, and failed submissions reduce perceived value.

The findings confirm that perceived value mediates the relationship between service quality and behavioral intentions. Thus, students' intention to continue using digital learning platforms depends not only on service quality itself, but also on whether they perceive the platform as useful, efficient, supportive, and worth using for academic purposes.

The extended SEM model shows that perceived platform error exposure improves explanatory performance, highlighting the need to examine both positive service attributes and negative technical experiences. Theoretically, this study positions platform error exposure as a distinct negative user-experience construct. Practically, universities and platform providers should improve service quality, reduce recurring technical errors, and use proactive monitoring, routine audits, backup systems, and transparent communication to support sustainable platform adoption.

ACKNOWLEDGMENTS

The authors would like to express their deepest gratitude to the University, participants and colleagues for their exceptional support and resources, which were critical in facilitating this research.

CONFLICTS OF INTEREST

The authors declare that no conflicts of interest are associated with this study. All aspects of the research were conducted with the utmost integrity and transparency.

DATA AVAILABILITY

The datasets utilized and analyzed during this research are available from the corresponding author upon reasonable request.

ETHICAL STATEMENTS

The study received ethical approval from the relevant University Ethics Committee prior to data collection. All participants provided electronic informed consent before completing the survey.

FUNDING

This research was conducted without financial support. The authors confirm that no funding was received for this study's research, analysis, or publication.

REFERENCES

[1] A. O. Mohmmed, B. A. Khidhir, A. Nazeer, and V. J. Vijayan, "Emergency remote teaching during Coronavirus pandemic: the current trend and future directive at Middle East College Oman," Innov. Infrastruct. Solut., vol. 5, no. 3, p. 72, 2020, https://doi.org/10.1007/s41062-020-00326-7

[2] D. R. Garrison and H. Kanuka, "Blended learning: Uncovering its transformative potential in higher

education," Internet High. Educ., vol. 7, no. 2, pp. 95–105, 2004, https://doi.org/10.1016/j.iheduc.2004.02.001

[3] C. B. Hodges, S. Moore, B. B. Lockee, T. Trust, and M. A. Bond, "The difference between emergency remote teaching and online learning," Handb. Res. Online Learn. Insights Adv., vol. 27, no. 1, pp. 511–522, 2024, https://doi.org/10.1163/9789004702813_021

[4] K. A. Pituch and Y. kuei Lee, "The influence of system characteristics on e-learning use," Comput. Educ., vol. 47, no. 2, pp. 222–244, 2006, https://doi.org/10.1016/j.compedu.2004.10.007

[5] H. M. Selim, "Critical success factors for e-learning acceptance: Confirmatory factor models," Comput. Educ., vol. 49, no. 2, pp. 396–413, 2007, https://doi.org/10.1016/j.compedu.2005.09.004

[6] S. Ozkan and R. Koseler, "Multi-dimensional evaluation of E-learning systems in the higher education context: An empirical investigation of a computer literacy course," Proc. - Front. Educ. Conf. FIE, vol. 53, no. 4, pp. 1285–1296, 2009, https://doi.org/10.1109/FIE.2009.5350590

[7] S. S. Liaw, "Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: A case study of the Blackboard system," Comput. Educ., vol. 51, no. 2, pp. 864–873, 2008, https://doi.org/10.1016/j.compedu.2007.09.005

[8] C. Thangave et al., "Students' Activeness Measure in Moodle Learning Management System Using Machine Learning," J. Appl. Eng. Technol. Sci., vol. 6, no. 1, pp. 744–753, 2024, https://doi.org/10.37385/jaets.v6i1.6128

[9] W. H. DeLone and E. R. McLean, "The DeLone and McLean model of information systems success: A ten-year update," J. Manag. Inf. Syst., vol. 19, no. 4, pp. 9–30, 2003, https://doi.org/10.1080/07421222.2003.11045748

[10] N. Urbach and B. Müller, "The Updated DeLone and McLean Model of Information Systems Success," in Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1, Springer, 2012, pp. 1–18. https://doi.org/10.1007/978-1-4419-6108-2_1

[11] S. Petter, W. DeLone, and E. McLean, "Measuring information systems success: Models, dimensions, measures, and interrelationships," Eur. J. Inf. Syst., vol. 17, no. 3, pp. 236–263, 2008, https://doi.org/10.1057/ejis.2008.15

[12] R. D. Freeze, K. a Alshare, P. L. Lane, and H. Joseph Wen, "IS success model in e-learning context based on students' perceptions," J. Inf. Syst. Educ., vol. 21, no. 2, p. 173, 2010. https://jise.org/Volume21/n2/JISEv21n2p173.html

[13] W. A. Cidral, T. Oliveira, M. Di Felice, and M. Aparicio, "E-learning success determinants: Brazilian empirical study," Comput. Educ., vol. 122, pp. 273–290, 2018, https://doi.org/10.1016/j.compedu.2017.12.001

[14] A. Hassanzadeh, F. Kanaani, and S. Elahi, "A model for measuring e-learning systems success in universities," Expert Syst. Appl., vol. 39, no. 12, pp. 10959–10966, 2012. https://doi.org/10.1016/j.eswa.2012.03.028

[15] P. C. Sun, R. J. Tsai, G. Finger, Y. Y. Chen, and D. Yeh, "What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction," Comput. Educ., vol. 50, no. 4, pp. 1183–1202, May 2008. https://doi.org/10.1016/j.compedu.2006.11.007

[16] Z. Shi and H. Shang, "A review on quality of service and servqual model," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2020, vol. 12204 LNCS, pp. 188–204. https://doi.org/10.1007/978-3-030-50341-3_15

[17] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality," J. Retail., vol. 64, no. 1, pp. 12–40, 1988. https://www.econbiz.de/10001056853

[18] J. J. Cronin, M. K. Brady, and G. T. M. Hult, "Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments," J. Retail., vol. 76, no. 2, pp. 193–218, 2000, https://doi.org/10.1016/S0022-4359(00)00028-2

[19] R. Novendra, N. Jalinus, Waskito, Afriansyah, and A. Rasfira, "User Satisfaction Analysis of Service Quality of Dapodik Applications (Educational Data) Using Servqual Method," J. Appl. Eng. Technol. Sci., vol. 3, no. 2, pp. 190–194, 2022, https://doi.org/10.37385/jaets.v3i2.790

[20] D. Al-Fraihat, M. Joy, and J. Sinclair, "Evaluating E-learning systems success: An empirical study," Comput. Human Behav., vol. 102, pp. 67–86, 2020. https://doi.org/10.1016/j.chb.2019.08.004

[21] A. Y. Alsabawy, A. Cater-Steel, and J. Soar, "Determinants of perceived usefulness of e-learning systems," Comput. Human Behav., vol. 64, pp. 843–858, 2016, https://doi.org/10.1016/j.chb.2016.07.065

[22] L. Pham, Y. B. Limbu, T. K. Bui, H. T. Nguyen, and H. T. Pham, "Does e-learning service quality influence e-learning student satisfaction and loyalty? Evidence from Vietnam," Int. J. Educ. Technol. High. Educ., vol. 16, no. 1, pp. 1–26, 2019, https://doi.org/10.1186/s41239-019-0136-3

[23] J. C. Sweeney and G. N. Soutar, "Consumer perceived value: The development of a multiple item scale," J. Retail., vol. 77, no. 2, pp. 203–220, 2001, https://doi.org/10.1016/S0022-4359(01)00041-0

[24] R. B. Woodruff, "Customer value: The next source for competitive advantage," J. Acad. Mark. Sci., vol. 25, no. 2, pp. 139–153, 1997, https://doi.org/10.1007/BF02894350

[25] M. C. Kim, M. J. Hannafin, and L. A. Bryan, "Technology-enhanced inquiry tools in science education: An emerging pedagogical framework for classroom practice," Sci. Educ., vol. 91, no. 6, pp. 1010–1030, 2007, https://doi.org/10.1002/sce.20219

[26] R. L. Oliver, "A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions," J. Mark. Res., vol. 17, no. 4, p. 460, 1980, https://doi.org/10.2307/3150499

[27] M. A. Hossain and M. Quaddus, "Expectation–Confirmation Theory in Information System Research: A Review and Analysis," Inf. Syst. theory Explain. Predict. our Digit. Soc. Vol. 1, pp. 441–469, 2012, https://doi.org/10.1007/978-1-4419-6108-2_21

[28] A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," MIS Q. Manag. Inf. Syst., vol. 25, no. 3, pp. 351–370, 2001, https://doi.org/10.2307/3250921

[29] C. M. Chiu, M. H. Hsu, S. Y. Sun, T. C. Lin, and P. C. Sun, "Usability, quality, value and e-learning continuance

decisions," Comput. Educ., vol. 45, no. 4, pp. 399–416, 2005, https://doi.org/10.1016/j.compedu.2004.06.001
[30] J. C. Roca, C.-M. Chiu, and F. J. Martínez, "Understanding e-learning continuance intention: An extension of the Technology Acceptance Model," Int. J. Hum. Comput. Stud., vol. 64, no. 8, pp. 683–696, 2006. https://doi.org/10.1016/j.ijhcs.2006.01.003
[31] S. Petter and E. R. McLean, "A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level," Inf. Manag., vol. 46, no. 3, pp. 159–166, 2009, https://doi.org/10.1016/j.im.2008.12.006
[32] R. Ayyagari, V. Grover, and R. Purvis, "Technostress: Technological antecedents and implications," MIS Q. Manag. Inf. Syst., vol. 35, no. 4, pp. 831–858, 2011, https://doi.org/10.2307/41409963
[33] P. Sanjeeva Kumar, "TECHNOSTRESS: A comprehensive literature review on dimensions, impacts, and management strategies," Comput. Hum. Behav. Reports, vol. 16, p. 100475, 2024, https://doi.org/10.1016/j.chbr.2024.100475
[34] S. C. Srivastava, S. Chandra, and A. Shirish, "Technostress creators and job outcomes: Theorising the moderating influence of personality traits," Inf. Syst. J., vol. 25, no. 4, pp. 355–401, 2015, https://doi.org/10.1111/isj.12067
[35] M. Tarafdar, Q. Tu, and T. Ragu-Nathan, "Impact of technostress on end-user satisfaction and performance," J. Manag. Inf. Syst., vol. 27, no. 3, pp. 303–334, 2010, https://doi.org/10.2753/MIS0742-1222270311
[36] B. Al-shargabi, O. Sabri, and S. Aljawarneh, "The adoption of an e-learning system using information systems success model: a case study of Jazan University," PeerJ Comput. Sci., vol. 7, pp. 1–21, 2021, https://doi.org/10.7717/peerj-cs.723
[37] G. Chopra, P. Madan, P. Jaisingh, and P. Bhaskar, "Effectiveness of e-learning portal from students' perspective: A structural equation model (SEM) approach," Interact. Technol. Smart Educ., vol. 16, no. 2, pp. 94–116, 2019, https://doi.org/10.1108/ITSE-05-2018-0027
[38] F. Amastini, D. K. S. Sekarhati, and M. Puspitasari, "Advancing Adaptive and Personalized E-Learning Systems: A Systematic Literature Review," Adv. Sustain. Sci. Eng. Technol., vol. 7, no. 2, 2025, https://doi.org/10.26877/m82zg802
[39] V. A. Zeithaml, L. L. Berry, and A. Parasuraman, "The Behavioral Consequences of Service Quality," J. Mark., vol. 60, no. 2, pp. 31–46, 1996, https://doi.org/10.1177/002224299606000203
[40] T. J. McGill and J. E. Klobas, "A task-technology fit view of learning management system impact," Comput. Educ., vol. 52, no. 2, pp. 496–508, 2009, https://doi.org/10.1016/j.compedu.2008.10.002
[41] P. D. Simon, J. Jiang, L. K. Fryer, R. B. King, and C. E. Frondozo, "An Assessment of Learning Management System Use in Higher Education: Perspectives from a Comprehensive Sample of Teachers and Students," Technol. Knowl. Learn., vol. 30, no. 2, pp. 741–767, 2025, https://doi.org/10.1007/s10758-024-09734-5
[42] A. AL-Hawamleh, "Exploring the Satisfaction and Continuance Intention to Use E-Learning Systems," Int. J. Electr. Comput. Eng. Syst., vol. 15, no. 2, pp. 201–214, 2024, https://doi.org/10.32985/ijeces.15.2.8
[43] M. A. Alterkait and M. Y. Alduaij, "Impact of Information Quality on Satisfaction with E-Learning Platforms: Moderating Role of Instructor and Learner Quality," SAGE Open, vol. 14, no. 1, p. 21582440241233400, 2024, https://doi.org/10.1177/21582440241233400
[44] A. R. Alkhuwaylidee, "Exploring Factors Influencing Students' Continuance Intention to Use E-Learning System for Iraqi University Students," Computers, vol. 14, no. 5, p. 176, 2025, https://doi.org/10.3390/computers14050176
[45] E. Novak, K. McDaniel, and J. Li, "Factors that impact student frustration in digital learning environments," Comput. Educ. Open, vol. 5, p. 100153, 2023, https://doi.org/10.1016/j.caeo.2023.100153
[46] F. Saleem, E. Chikhaoui, and M. I. Malik, "Technostress in students and quality of online learning: role of instructor and university support," in Frontiers in Education, 2024, vol. 9, p. 1309642. https://doi.org/10.3389/feduc.2024.1309642
[47] S. Yan, L. G. Eng, and L. C. Seong, "Influencing Factors of Continuous Intention to Use E-learning System of Undergraduates in Guangxi, China: The Mediating Role of Perceived Ease of Use and Perceived Usefulness," SAGE Open, vol. 14, no. 4, p. 21582440241305230, 2024, https://doi.org/10.1177/21582440241305231
[48] A. AlMulhem, "Investigating the effects of quality factors and organizational factors on university students' satisfaction of e-learning system quality," Cogent Educ., vol. 7, no. 1, p. 1787004, 2020, https://doi.org/10.1080/2331186X.2020.1787004
[49] R. E. Sewandono, A. Thoyib, D. Hadiwidjojo, and A. Rofiq, "Performance expectancy of E-learning on higher institutions of education under uncertain conditions: Indonesia context," Educ. Inf. Technol., vol. 28, no. 4, pp. 4041–4068, 2023, https://doi.org/10.1007/s10639-022-11074-9
[50] A. Bhattacherjee and A. Barfar, "Information Technology Continuance Research: Current State and Future Directions," Asia Pacific J. Inf. Syst., vol. 21, no. 2, pp. 1–18, 2011. https://apjis.or.kr/pdf/MIS021-002-1.pdf
[51] A. Patricia Aguilera-Hermida, "College students' use and acceptance of emergency online learning due to COVID-19," Int. J. Educ. Res. Open, vol. 1, p. 100011, 2020, https://doi.org/10.1016/j.ijedro.2020.100011
[52] M. Henderson, N. Selwyn, and R. Aston, "What works and why? Student perceptions of 'useful' digital technology in university teaching and learning," Stud. High. Educ., vol. 42, no. 8, pp. 1567–1579, 2017, https://doi.org/10.1080/03075079.2015.1007946
[53] M. Tarafdar, Q. Tu, B. S. Ragu-Nathan, and T. S. Ragu-Nathan, "The impact of technostress on role stress and productivity," J. Manag. Inf. Syst., vol. 24, no. 1, pp. 301–328, 2007, https://doi.org/10.2753/MIS0742-1222240109
[54] V. A. Zeithaml, "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence," J. Mark., vol. 52, no. 3, p. 2, 1988, https://doi.org/10.2307/1251446
[55] M. Al Amin, M. Razib Alam, and M. Z. Alam, "Antecedents of students' e-learning continuance intention during COVID-19: An empirical study," E-Learning Digit. Media, vol. 20, no. 3, pp. 224–254, 2023, https://doi.org/10.1177/20427530221103915

[56] S. A. Issa and H. A. El-Sabagh, "Design an adaptive e-learning environment based on personalized factors and its impact on the development of students' metacognitive thinking skills," in Frontiers in Education, 2026, vol. 11, p. 1765181. https://doi.org/10.3389/feduc.2026.1765181

[57] J. Dai, X. Zhang, and C. Wang, "A meta-analysis of learners' continuance intention toward online education platforms," Educ. Inf. Technol., vol. 29, no. 16, pp. 21833–21868, 2024, https://doi.org/10.1007/s10639-024-12654-7

[58] M. Guo, "The Influence of Educational and Emotional Support on e-Learning Continuance Intention: A Two-Stage Approach PLS-SEM and ANN Analysis," SAGE Open, vol. 14, no. 4, p. 21582440241280790, 2024, https://doi.org/10.1177/21582440241280793

[59] G. Pan, Y. Mao, Z. Song, and H. Nie, "Research on the influencing factors of adult learners' intent to use online education platforms based on expectation confirmation theory," Sci. Rep., vol. 14, no. 1, p. 12762, 2024, https://doi.org/10.1038/s41598-024-63747-9

[60] R. Song and Y. Zheng, "Predicting Continuance Intention to Use Learning Management Systems among Undergraduates: The Moderating Effect of Intrinsic Motivation," SAGE Open, vol. 14, no. 3, p. 21582440241271320, 2024, https://doi.org/10.1177/21582440241271319

[61] L. T. Vu, L. Pham, M. Á. Zúñiga, and T. T. T. Nguyen, "The Mediating Roles of E-Learning Student Perceived Value on the Relationship Between E-Learning Service Quality Attributes and E-Learning Student Loyalty," J. Consum. Satisf. Dissatisfaction Complain. Behav., vol. 38, no. 1, pp. 123–148, 2025. https://jcsdcb.com/index.php/JCSDCB/article/view/1066

[62] N. Bouranta, E. L. Psomas, and D. Kafetzopoulos, "Integrating online learning into service quality assessment in higher-education its influence on student satisfaction," TQM J., vol. 37, no. 5, pp. 1418–1445, 2025, https://doi.org/10.1108/TQM-06-2023-0180

[63] F. Fitria, M. Yahya, M. I. Ali, P. Purnamawati, and A. M. Mappalotteng, "The Impact of System Quality and User Satisfaction: The Mediating Role of Ease of Use and Usefulness in E-Learning Systems," Int. J. Environ. Eng. Educ., vol. 6, no. 2, pp. 119–131, 2024. https://doi.org/10.55151/ijeedu.v6i2.134

[64] P. Dangaiso, F. Makudza, and H. Hogo, "Modelling perceived e-learning service quality, student satisfaction and loyalty. A higher education perspective," Cogent Educ., vol. 9, no. 1, p. 2145805, 2022, https://doi.org/10.1080/2331186X.2022.2145805

[65] A. A. Yunusa and I. N. Umar, "A scoping review of critical predictive factors (CPFs) of satisfaction and perceived learning outcomes in E-learning environments," Educ. Inf. Technol., vol. 26, no. 1, pp. 1223–1270, 2021. https://doi.org/10.1007/s10639-020-10286-1

[66] A. Obeid, R. Ibrahim, and A. Fadhil, "Extended Model of Expectation Confirmation Model to Examine Users' Continuous Intention Toward the Utilization of E-Learning Platforms," IEEE Access, vol. 12, pp. 40752–40764, 2024, https://doi.org/10.1109/ACCESS.2024.3373190

[67] J. Y. L. Thong, S. J. Hong, and K. Y. Tam, "The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance," Int. J. Hum. Comput. Stud., vol. 64, no. 9, pp. 799–810, 2006, https://doi.org/10.1016/j.ijhcs.2006.05.001

[68] G. Daɪhan and B. Akkoyunlu, "Modeling the continuance usage intention of online learning environments," Comput. Human Behav., vol. 60, pp. 198–211, 2016, https://doi.org/10.1016/j.chb.2016.02.066

[69] K. M. Lin, "E-Learning continuance intention: Moderating effects of user e-learning experience," Comput. Educ., vol. 56, no. 2, pp. 515–526, 2011, https://doi.org/10.1016/j.compedu.2010.09.017

[70] H. Landrum and V. R. Prybutok, "A service quality and success model for the information service industry," Eur. J. Oper. Res., vol. 156, no. 3, pp. 628–642, 2004, https://doi.org/10.1016/S0377-2217(03)00125-5

[71] M. Tarafdar, E. B. Pullins, and T. S. Ragu-Nathan, "Technostress: Negative effect on performance and possible mitigations," Inf. Syst. J., vol. 25, no. 2, pp. 103–132, 2015, https://doi.org/10.1111/isj.12042

[72] M. Salanova, S. Llorens, and E. Cifre, "The dark side of technologies: Technostress among users of information and communication technologies," Int. J. Psychol., vol. 48, no. 3, pp. 422–436, 2013, https://doi.org/10.1080/00207594.2012.680460

[73] H. N. Sabeh, M. H. Husin, D. M. H. Kee, A. S. Baharudin, and R. Abdullah, "A Systematic Review of the DeLone and McLean Model of Information Systems Success in an E-Learning Context (2010-2020)," IEEE Access, vol. 9, pp. 81210–81235, 2021, https://doi.org/10.1109/ACCESS.2021.3084815

[74] G. J. Udo, K. K. Bagchi, and P. J. Kirs, "Using SERVQUAL to assess the quality of e-learning experience," Comput. Human Behav., vol. 27, no. 3, pp. 1272–1283, 2011.

[75] M. C. Lee, "Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model," Comput. Educ., vol. 54, no. 2, pp. 506–516, 2010, https://doi.org/10.1016/j.compedu.2009.09.002

[76] T. S. Ragu-Nathan, M. Tarafdar, B. S. Ragu-Nathan, and Q. Tu, "The consequences of technostress for end users in organizations: Conceptual development and validation," Inf. Syst. Res., vol. 19, no. 4, pp. 417–433, 2008, https://doi.org/10.1287/isre.1070.0165

[77] W. H. DeLone and E. R. McLean, "Information Systems Success Measurement," Inf. Syst. Success Meas., vol. 2, no. 1, pp. 1–116, 2016, https://doi.org/10.1561/9781680831436

[78] S. H. Alshammari and R. A. Alshammari, "An integration of expectation confirmation model and information systems success model to explore the factors affecting the continuous intention to utilise virtual classrooms," Sci. Rep., vol. 14, no. 1, p. 18491, 2024, https://doi.org/10.1038/s41598-024-69401-8

[79] T. D. Vu, B. K. Nguyen, P. T. Vu, T. M. N. Nguyen, and C. C. Hoang, "Promoting customer satisfaction and reuse intention using ride-hailing taxi services: role of consumer perceived value, personal innovativeness and corporate image," Asia-Pacific J. Bus. Adm., vol. 17, no. 4, pp. 1021–1047, 2025, https://doi.org/10.1108/APJBA-11-2023-0570

[80] L. Li, "What are the Key Drivers to Promote Continuance Intention of Undergraduates in Mobile Learning? A Multi-perspective Framework," SAGE Open, vol. 14, no. 4, p. 1121614, 2024,

https://doi.org/10.1177/21582440241280656
[81] J. Zhang, M. Zhang, Y. Liu, and L. Zhang, "What are the key drivers to promote continuance intention of undergraduates in online learning? A multi-perspective framework," Front. Psychol., vol. 14, p. 1121614, 2023, https://doi.org/10.3389/fpsyg.2023.1121614
[82] K. Kim, S. Trimi, H. Park, and S. Rhee, "The Impact of CMS Quality on the Outcomes of E-learning Systems in Higher Education: An Empirical Study," Decis. Sci. J. Innov. Educ., vol. 10, no. 4, pp. 575–587, 2012, https://doi.org/10.1111/j.1540-4609.2012.00360.x
[83] I. Rodríguez-Ardura and A. Meseguer-Artola, "What leads people to keep on e-learning? An empirical analysis of users' experiences and their effects on continuance intention," Interact. Learn. Environ., vol. 24, no. 6, pp. 1030–1053, 2016, https://doi.org/10.1080/10494820.2014.926275
[84] H. Mohammadi, "Investigating users' perspectives on e-learning: An integration of TAM and IS success model," Comput. Human Behav., vol. 45, pp. 359–374, 2015, https://doi.org/10.1016/j.chb.2014.07.044
[85] N. Lankton, D. H. McKnight, and J. B. Thatcher, "Incorporating trust-in-technology into Expectation Disconfirmation Theory," J. Strateg. Inf. Syst., vol. 23, no. 2, pp. 128–145, 2014, https://doi.org/10.1016/j.jsis.2013.09.001
[86] B. Wu and C. Zhang, "Empirical study on continuance intentions towards E-Learning 2.0 systems," Behav. Inf. Technol., vol. 33, no. 10, pp. 1027–1038, 2014, https://doi.org/10.1080/0144929X.2014.934291
[87] K. H. Yuan and L. Deng, "Equivalence of Partial-Least-Squares SEM and the Methods of Factor-Score Regression," Struct. Equ. Model., vol. 28, no. 4, pp. 557–571, 2021, https://doi.org/10.1080/10705511.2021.1894940
[88] R. B. Kline, Principles and practice of structural equation modeling. Guilford publications, 2023. https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462551910
[89] Z. Yuan, X. Deng, T. Ding, J. Liu, and Q. Tan, "Factors influencing secondary school teachers' usage behavior of dynamic mathematics software: A partial least squares structural equation modeling (PLS-SEM) method," Electron. Res. Arch., vol. 31, no. 9, pp. 5649–5684, 2023, https://doi.org/10.3934/era.2023287
[90] X. Tang, Z. Yuan, X. Deng, and L. Xiang, "Predicting secondary school mathematics teachers' digital teaching behavior using partial least squares structural equation modeling," Electron. Res. Arch., vol. 31, no. 10, pp. 6274–6302, 2023, https://doi.org/10.3934/era.2023318
[91] E. J. Wolf, K. M. Harrington, S. L. Clark, and M. W. Miller, "Sample Size Requirements for Structural Equation Models: An Evaluation of Power, Bias, and Solution Propriety," Educ. Psychol. Meas., vol. 73, no. 6, pp. 913–934, 2013, https://doi.org/10.1177/0013164413495237
[92] J. F. Hair, B. J. Babin, R. E. Anderson, and W. C. Black, Multivariate Data Analysis. Belmont, CA: Cengage Learning, 2022. https://www.cengage.uk/c/multivariate-data-analysis-8e-hair-babin-anderson-black/9781473756540/
[93] N. Chopra, R. Sindwani, and M. Goel, "Integrating MOOC service quality as a second-order factor in learner engagement, satisfaction and retention model: a moderated sequential multiple mediation model," Kybernetes, 2025, https://doi.org/10.1108/K-11-2024-2982
[94] A. Bhattacherjee, "Understanding information systems continuance," MIS Q., vol. 25, no. 3, pp. 351–370, 2001, https://doi.org/10.2307/3250921
[95] G. O. Boateng, T. B. Neilands, E. A. Frongillo, H. R. Melgar-Quiñonez, and S. L. Young, "Best Practices for Developing and Validating Scales for Health, Social, and Behavioral Research: A Primer," Front. Public Heal., vol. 6, p. 149, 2018, https://doi.org/10.3389/fpubh.2018.00149
[96] R. F. DeVellis and C. T. Thorpe, Scale development: Theory and applications. Sage publications, 2021. https://uk.sagepub.com/en-gb/eur/scale-development/book269114
[97] P. M. Podsakoff, S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff, "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," J. Appl. Psychol., vol. 88, no. 5, pp. 879–903, 2003, https://doi.org/10.1037/0021-9010.88.5.879
[98] M. Rhemtulla, P. É. Brosseau-Liard, and V. Savalei, "When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions," Psychol. Methods, vol. 17, no. 3, pp. 354–373, 2012, https://doi.org/10.1037/a0029315
[99] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," Struct. Equ. Model., vol. 6, no. 1, pp. 1–55, 1999, https://doi.org/10.1080/10705519909540118
[100] C. Fornell and D. F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," J. Mark. Res., vol. 18, no. 1, p. 39, 1981, https://doi.org/10.2307/3151312
[101] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," J. Acad. Mark. Sci., vol. 43, no. 1, pp. 115–135, 2015, https://doi.org/10.1007/s11747-014-0403-8
[102] J. Cohen, Statistical power analysis for the behavioral sciences, 2nd ed. Hillsdale, New Jersey: Lawrence Erlbaum Associates, 1988. https://doi.org/10.4324/9780203771587
[103] A. Satorra and P. M. Bentler, "A scaled difference chi-square test statistic for moment structure analysis," Psychometrika, vol. 66, no. 4, pp. 507–514, 2001, https://doi.org/10.1007/BF02296192
[104] G. W. Cheung and R. B. Rensvold, "Evaluating goodness-of-fit indexes for testing measurement invariance," Struct. Equ. Model., vol. 9, no. 2, pp. 233–255, 2002, https://doi.org/10.1207/S15328007SEM0902_5
[105] F. F. Chen, "Sensitivity of goodness of fit indexes to lack of measurement invariance," Struct. Equ. Model., vol. 14, no. 3, pp. 464–504, 2007, https://doi.org/10.1080/10705510701301834
[106] C. Wang, J. Dai, K. Zhu, T. Yu, and X. Gu, "Understanding the Continuance Intention of College Students toward New E-Learning Spaces Based on an Integrated Model of the TAM and TTF," Int. J. Hum. Comput. Interact., vol. 40,

no. 24, pp. 8419–8432, 2024, https://doi.org/10.1080/10447318.2023.2291609
[107] X. Wang and X. Yu, "Art Students' Technostress, Perceived Usefulness, Satisfaction, and Continuance Intention to Use Mobile Educational Applications," SAGE Open, vol. 14, no. 2, p. 21582440241260210, 2024, https://doi.org/10.1177/21582440241260206

SUPPLEMENTARY

Table S1. Complete measurement items, construct dimensions, item codes, and adaptation sources used in the survey instrument.

Construct	Dimension	Code	Measurement Item	Adaptation Source
Service Quality	Reliability	REL1	The platform performs reliably during learning activities.	Adapted from DeLone and McLean (2003) [9] and the SERVQUAL tradition Parasuraman et al., (1988) [17].
		REL2	The platform provides consistent access to learning materials.	
		REL3	The platform functions properly when I need to complete learning tasks.	
	Responsiveness	RES1	The platform responds quickly when I access learning materials.	Adapted from DeLone and McLean (2003) [9] and the SERVQUAL tradition Parasuraman et al., (1988) [17].
		RES2	Technical support promptly responds to platform-related issues.	
		RES3	The platform provides timely responses to student learning needs.	
		RES4	Problems related to platform use are addressed without unnecessary delay.	
	Assurance	ASS1	I feel confident using the platform for learning activities.	Adapted from DeLone and McLean (2003) [9] and the SERVQUAL tradition Parasuraman et al., (1988) [17].
		ASS2	The platform provides a trustworthy digital learning environment.	
		ASS3	The platform gives me confidence that I can complete my learning tasks properly.	
	Empathy	EMP1	The platform supports students' learning needs.	Adapted from DeLone and McLean (2003) [9] and the SERVQUAL tradition Parasuraman et al., (1988) [17].
		EMP2	The platform offers features suitable for students' academic needs.	
		EMP3	The platform helps students complete learning activities conveniently.	
	Tangibility	TAN1	The platform interface is clear and well-organized.	Adapted from DeLone and McLean (2003) [9] and the SERVQUAL tradition Parasuraman et al., (1988) [17].
		TAN2	The platform design makes learning materials easy to access.	
		TAN3	The platform provides a visually accessible and user-friendly learning environment.	
Perceived Value		PV1	Using the platform is valuable for my learning.	Adapted from Bhattacherjee (2001) [28].
		PV2	The platform provides useful support for my academic activities.	
		PV3	The benefits of using the platform are greater than the effort required to use it.	
		PV4	The platform helps me complete learning tasks efficiently.	
		PV5	Overall, the platform provides good value for my learning experience.	

Construct	Dimension	Code	Measurement Item	Adaptation Source
Behavioral Intentions		BI1	I intend to continue using this platform for learning activities.	Adapted from Zeithaml et al. (1996) [39].
		BI2	I would recommend this platform to other students.	
		BI3	I am likely to use this platform again in future learning activities.	
		BI4	I would choose to use this platform when it is available for my courses.	
Perceived Platform Error Exposure		FE1	The platform crashes or freezes during use.	Developed in this study through systems-engineering-informed item development, expert review (Boateng et al., 2018 [95]; DeVellis, 2017 [96]).
		FE2	Video content or learning pages buffer or load slowly on the platform.	
		FE3	Errors occur when I submit assignments, access links, or complete learning tasks on the platform.	

Table S2. Item-level standardized factor loadings and construct-level reliability and convergent validity statistics.

Construct	Item	Standardized Loading	C.R	AVE	Cronbach's α
Reliability (REL)	REL1	0.841	0.893	0.677	0.891
	REL2	0.823			
	REL3	0.804			
Responsiveness (RES)	RES1	0.856	0.907	0.662	0.904
	RES2	0.812			
	RES3	0.789			
	RES4	0.797			
Assurance (ASS)	ASS1	0.868	0.906	0.708	0.903
	ASS2	0.837			
	ASS3	0.818			
Empathy (EMP)	EMP1	0.791	0.861	0.609	0.857
	EMP2	0.804			
	EMP3	0.747			
Tangibility (TAN)	TAN1	0.812	0.871	0.631	0.868
	TAN2	0.795			
	TAN3	0.775			
Perceived Value (PV)	PV1	0.862	0.924	0.710	0.921
	PV2	0.847			
	PV3	0.831			
	PV4	0.819			
	PV5	0.853			
Behavioral Intentions (BI)	BI1	0.887	0.932	0.774	0.930
	BI2	0.869			
	BI3	0.894			
	BI4	0.868			
Perceived Platform Error Exposure (FERR)	FE1	0.891	0.908	0.766	0.905
	FE2	0.874			
	FE3	0.862			