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Research Article

The Persistence Architecture of E-Learning: Linking Quality, Acceptance, and Student Satisfaction

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ABSTRACT

E-learning sustainability depends on students' post-adoption evaluations of platform performance, information quality, usefulness, satisfaction, and continued use. This study examines students' continuance intention toward institutional e-learning systems by integrating the Technology Acceptance Model and the Information Systems Success Model. A quantitative explanatory survey was conducted with 470 students from five Indonesian universities. Data were analyzed using covariance-based structural equation modeling with IBM SPSS and AMOS. The final model showed excellent fit (CMIN/DF = 1.036, CFI = 0.999, TLI = 0.999, RMSEA = 0.009). The results reveal that information quality was the dominant driver of perceived usefulness ($\beta = 0.824$, $p < 0.001$) and also significantly improved perceived ease of use ($\beta = 0.321$, $p < 0.001$). User satisfaction strongly predicted continuance intention ($\beta = 0.612$, $p < 0.001$), while perceived usefulness substantially increased satisfaction ($\beta = 0.475$, $p < 0.001$). By contrast, system quality had only weak effects on perceived ease of use ($\beta = 0.164$) and perceived usefulness ($\beta = 0.072$), and perceived ease of use had a negligible effect on satisfaction ($\beta = 0.019$). These findings show that sustained e-learning use is shaped primarily by the quality and academic value of information rather than by technical functionality alone. The study refines TAM–ISSM integration by identifying a clear information quality–usefulness–satisfaction–continuance pathway in post-adoption settings. Universities should therefore prioritize relevant, accurate, well-organized, and timely learning content, while maintaining reliable system performance, to strengthen student satisfaction and long-term engagement.

KEYWORDS information quality • perceived usefulness • perceived ease of use • post-adoption behavior • system quality • user satisfaction • structural equation modeling

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1. INTRODUCTION

E-learning systems have become integral to higher education as universities increasingly employ digital platforms to support flexible, accessible, and technology-mediated learning. These systems have altered the delivery of instructional materials, coordination of learning activities, facilitation of academic interaction, and provision of educational resources beyond temporal and geographical constraints [1]–[4]. Their functions extend beyond content distribution to include communication, assessment, feedback, collaboration, and independent learning [5]–[7]. E-learning systems can therefore be positioned as institutional learning infrastructure rather than supplementary instructional media.

The increasing institutional dependence on e-learning systems has shifted attention from initial adoption to sustained use. Initial use may result from institutional requirements and does not necessarily indicate voluntary acceptance or long-term engagement [8]–[10]. Continued use depends on students' evaluations of whether a system is useful, easy to operate, technically reliable, and capable of providing relevant academic information [11], [12]. Technical failures, ambiguous instructions, inefficient navigation, delayed system responses, and unsatisfactory prior experiences may reduce students' intention to continue using the platform [13]. Identifying the determinants of user satisfaction and continuance intention is therefore necessary for evaluating the long-term effectiveness of e-learning systems.

The Technology Acceptance Model (TAM) provides a theoretical basis for explaining users' acceptance of information technology. TAM identifies perceived usefulness and perceived ease of use as central cognitive beliefs that influence users' attitudes and behavioral intentions [14]. Perceived usefulness refers to the degree to which an individual believes that system use improves task performance, whereas perceived ease of use concerns the degree to which system operation is perceived as requiring minimal effort [14], [15]. In e-learning contexts, perceived usefulness reflects students' assessment that the platform facilitates access to learning materials, completion of academic tasks, learning efficiency, and achievement of learning objectives [16], [17]. Perceived ease of use reflects the perceived simplicity of learning, navigating, and operating the system [18]–[20]. Students are consequently more likely to evaluate an e-learning system positively when it provides identifiable academic benefits without imposing unnecessary operational complexity.

TAM does not, however, fully represent the system-related and information-related attributes that shape users' evaluations of information systems. The Information Systems Success Model (ISSM) addresses this limitation by conceptualizing information system success through system quality, information quality, service quality, use, user satisfaction, and net benefits [21], [22]. In e-learning environments, system quality encompasses technical reliability, responsiveness, accessibility, usability, interface performance, and navigation efficiency [2], [6], [23]. Information quality concerns the accuracy, relevance, completeness, clarity, organization, timeliness, and usefulness of the academic information delivered through the platform [22], [24]. These quality dimensions provide a structural explanation of how technical and informational characteristics may shape students' perceptions of usefulness, ease of use, and satisfaction.

The integration of TAM and ISSM provides a coherent framework for explaining students' continuance intention toward e-learning systems. TAM explains the formation of perceived usefulness and perceived ease of use, whereas ISSM identifies the quality characteristics that influence users' evaluations of system performance and information provision [11], [22]. In the proposed model, system quality and information quality are specified as external antecedents of perceived ease of use and perceived usefulness. These technology-related perceptions are subsequently linked to user satisfaction, which is positioned as the direct antecedent of continuance intention. This structural sequence reflects a post-adoption process in which continued use is shaped by accumulated evaluations of technical performance, information quality, functional benefits, interaction effort, and prior user experience [5], [8], [9], [25].

System quality represents a primary determinant of students' interaction with e-learning systems because technical performance directly structures the conditions under which learning activities are conducted. Reliable access, rapid system responses, consistent functionality, and efficient navigation can reduce operational barriers and support students' ability to complete academic tasks [2], [6], [23]. Previous studies have associated system quality with perceived usefulness, user satisfaction, and continued use in digital learning environments [24], [26]. Within the proposed model, system quality is expected to influence perceived ease of use because stable and usable system features reduce the effort required to access and manage learning activities. System quality is also expected to influence perceived usefulness because reliable system performance enables academic tasks to be completed more efficiently.

Information quality constitutes a distinct determinant because e-learning systems operate simultaneously as technological platforms and channels for academic content. Accurate, relevant, complete, logically organized, and timely information supports students in interpreting learning materials, following instructional requirements, completing assignments, and achieving course objectives [5], [6], [22]. Prior research has commonly linked information quality to perceived usefulness because high-quality information strengthens the functional value attributed to an information system

[23], [24]. Information quality may also be associated with perceived ease of use. Clearly structured materials, consistent information architecture, and easily retrievable academic content can reduce cognitive effort and navigation difficulty. The proposed model therefore specifies information quality as an antecedent of both perceived usefulness and perceived ease of use.

User satisfaction represents an evaluative response formed through prior interaction with an information system. It incorporates cognitive assessments of system performance and affective responses to the overall user experience [5], [24], [27]. Information systems research has consistently positioned satisfaction as an outcome of system quality, information quality, and user perceptions, as well as an antecedent of continued system use [8], [22], [28]. In e-learning contexts, satisfaction tends to increase when students perceive the system as useful, easy to operate, technically reliable, and capable of delivering appropriate learning information [2], [5], [29]. Perceived usefulness and perceived ease of use are therefore hypothesized to influence user satisfaction in the proposed structural model.

Continuance intention refers to the intention to maintain system use after initial adoption and direct experience [8], [30], [31]. This construct is analytically relevant to e-learning because institutional implementation does not necessarily produce sustained student engagement. Continued use is more likely when students are satisfied with prior experience and perceive that the platform provides meaningful academic benefits [11], [12], [32], [33]. A meta-analysis of learners' continuance intention toward online education platforms identified satisfaction and perceived usefulness as substantial predictors of continued use [9]. Studies integrating TAM and ISSM have similarly associated system quality, information quality, perceived usefulness, perceived ease of use, and satisfaction with continuance intention [11], [34]. These findings support a sequential explanation in which quality attributes shape technology perceptions, technology perceptions influence satisfaction, and satisfaction subsequently predicts continuance intention.

Despite the development of research on e-learning acceptance and information system success, several analytical gaps remain. First, a substantial proportion of the literature emphasizes initial technology acceptance rather than students' post-adoption evaluations and sustained-use intentions [8], [9], [12]. Second, the separate application of TAM and ISSM limits the explanation of how system and information quality influence technology-related perceptions and satisfaction [2], [15], [22]. Third, integrated TAM–ISSM models require further empirical evaluation to clarify the relative effects of system quality and information quality on perceived ease of use, perceived usefulness, user satisfaction, and continuance intention in higher education [11], [34]. Fourth, the relationship between information quality and perceived ease of use remains insufficiently specified, although coherent information structures may reduce cognitive effort and facilitate system navigation.

Indonesian higher education provides a relevant empirical context for examining these relationships. Universities have implemented e-learning systems to support online, blended, and technology-enhanced instruction. Students' experiences may nevertheless differ across institutions because of variation in digital infrastructure, platform configuration, content management, instructional practices, and institutional support. Studies conducted in Indonesia and other higher education contexts indicate that usability, perceived usefulness, satisfaction, and system-related attributes are associated with sustained e-learning use [12], [16], [17]. Evidence obtained from multiple universities can therefore provide a broader assessment of how students evaluate e-learning systems and which factors are associated with their intention to continue using them.

The present study is related to Fitria et al. [35], which analyzed the same dataset comprising 470 students from five Indonesian universities. The two studies differ in theoretical scope, structural specification, and dependent outcome. Fitria et al. (2024) examined the relationships among system quality, perceived ease of use, perceived usefulness, and user satisfaction, with specific attention to mediation effects [35]. The present study extends that analytical framework by incorporating information quality, specifying user satisfaction as the direct antecedent of continuance intention, and examining continuance intention as a post-adoption behavioral outcome. This distinction enables the current model to evaluate whether students' assessments of technical and informational quality are transmitted through technology perceptions and satisfaction toward sustained-use intentions.

This study examines students' continuance intention toward e-learning systems through an integrated TAM–ISSM framework. The structural model evaluates the effects of system quality and information quality on perceived ease of use and perceived usefulness, the effects of perceived ease of use and perceived usefulness on user satisfaction, and the effect of user satisfaction on continuance intention. System quality and information quality represent ISSM-based quality attributes. Perceived ease of use and perceived usefulness represent TAM-based technology perceptions. User satisfaction represents students' evaluative response to prior system use, whereas continuance intention represents the proposed post-adoption outcome.

The study is expected to provide three contributions. First, it specifies the relationships through which system quality and information quality may shape perceived ease of use and perceived usefulness in e-learning environments. Second, it evaluates user satisfaction as a mechanism connecting students' technology perceptions with continuance intention. Third, it provides empirical evidence from students enrolled at five Indonesian universities. The findings may support institutional evaluation of system performance, information organization, user satisfaction, and sustained e-learning use without assuming that initial adoption necessarily represents long-term acceptance.

2. LITERATURE REVIEW

2.1. E-Learning Systems in Higher Education

E-learning systems in higher education have developed from supplementary digital tools into institutional infrastructures that support access to learning materials, online interaction, assessment, feedback, collaboration, and independent learning. This development positions e-learning as a socio-technical learning environment that integrates technological platforms, instructional design, digital resources, user interaction, institutional support, and learner characteristics [2]–[4], [7], [36]–[38]. E-learning success consequently cannot be inferred solely from platform availability. Its academic value depends on whether the system provides reliable technical performance, relevant learning information, coherent content organization, efficient navigation, and adequate support for instructional activities.

Contemporary e-learning research has shifted from descriptive assessments of flexibility and accessibility toward evaluations of sustained academic use. Access beyond spatial and temporal boundaries does not necessarily produce continued engagement. E-learning effectiveness is instead associated with the combined influence of system quality, information quality, user perceptions, satisfaction, and post-adoption behavior [1], [2], [6]. Technical infrastructure and pedagogical content must therefore function as interdependent components. A technically reliable platform may provide limited academic value when its content is incomplete or irrelevant, whereas high-quality instructional content may remain underutilized when delivered through an unstable or operationally complex system.

Students' accumulated experience after initial adoption constitutes a central basis for evaluating e-learning success. Al-Fraihat et al. [2] proposed that e-learning systems should be assessed through an integrated consideration of quality dimensions, learner perceptions, satisfaction, and perceived benefits. Alkhawaja et al. [39] found that system quality influenced students' acceptance through perceived usefulness and perceived ease of use. Alotaibi and Alshahrani [40] similarly identified system quality, information quality, service quality, and user satisfaction as relevant determinants of e-learning platform success. These findings indicate that e-learning adoption represents an ongoing evaluative process in which students assess whether the system consistently supports their academic requirements.

Post-adoption evaluation is particularly relevant in higher education because initial system use may be mandated by institutional policy. Under such conditions, initial use may indicate compliance rather than voluntary acceptance. Continued use depends more directly on whether students perceive the system as useful, easy to operate, technically reliable, and capable of supporting academic tasks [8], [9], [11], [12]. Dai et al. [9] reported through meta-analytic evidence that satisfaction and perceived usefulness are among the principal predictors of learners' continuance intention toward online education platforms. E-learning research should therefore distinguish between initial adoption and sustained use by examining how direct experience with system quality and information quality shapes satisfaction and continuance intention.

2.2. Technology Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis [14], provides a widely applied framework for explaining users' acceptance of information technology. The model identifies perceived usefulness and perceived ease of use as central cognitive beliefs associated with users' attitudes and behavioral intentions. Perceived usefulness refers to the degree to which an individual believes that system use improves task performance, whereas perceived ease of use refers to the degree to which system operation is perceived as requiring minimal effort [14], [15]. These constructs have been applied across organizational information systems, digital services, and educational technologies [10], [15].

In e-learning contexts, perceived usefulness reflects students' assessment that a learning platform facilitates access to course materials, completion of academic tasks, learning efficiency, communication, and achievement of learning objectives. This construct is analytically relevant because students are more likely to evaluate a system positively when its academic benefits are identifiable. Platforms that accelerate access to instructional content, simplify assignment submission, facilitate academic communication, and support learning management are more likely to be perceived as useful [2], [16], [17]. Research on immersive and metaverse-integrated learning environments has similarly associated post-adoption evaluation and perceived usefulness with continuance intention [41]–[43]. Alkhuwaylidee [44] further reported that students' perceived usefulness was influenced by system quality, content quality, and confirmation of prior expectations.

Perceived ease of use concerns the cognitive and operational effort required to learn, navigate, and operate a system. In e-learning environments, this construct extends beyond interface usability because it reflects the extent to which technical procedures interfere with or facilitate academic activity. An intuitive and internally consistent platform allows students to allocate greater attention to learning tasks rather than system operation.

Simplified navigation, predictable functions, and clear interaction procedures can reduce operational barriers and support positive evaluations of system use [5], [14], [15]. Perceived ease of use may also strengthen perceived usefulness because a system that can be operated efficiently is more likely to be assessed as beneficial for academic work.

TAM has limited explanatory scope when applied independently to e-learning success. Although the model explains students' cognitive evaluations of technology, it does not specify the technical and informational conditions through which perceived usefulness and perceived ease of use are formed. In e-learning settings, these perceptions may be shaped by system reliability, accessibility, interface clarity, response speed, information accuracy, content relevance, completeness, feedback quality, and institutional support. Empirical studies have associated these system-level and information-level attributes with user satisfaction, technology acceptance, and continued e-learning use [45]–[49]. An information systems success perspective is therefore required to explain how quality-related characteristics function as antecedents of technology-related beliefs.

2.3. Information Systems Success Model

The Information Systems Success Model (ISSM), developed by DeLone and McLean [21] and subsequently updated by DeLone and McLean [22], conceptualizes information system success through several interrelated dimensions. The updated model comprises system quality, information quality, service quality, system use or intention to use, user satisfaction, and net benefits. This framework is applicable to e-learning because learning management systems operate simultaneously as technical platforms and academic information environments. Their success depends not only on usage frequency but also on the reliability of system functions, quality of academic information, responsiveness of support, user satisfaction, and perceived learning benefits.

System quality refers to the technical and functional performance of an information system. In e-learning environments, this construct commonly includes reliability, accessibility, response speed, system stability, interface design, flexibility, and navigation efficiency [1], [2], [6], [23]. A high-quality system enables students to access learning materials, interact with digital resources, and complete academic activities without avoidable technical disruption. System quality can therefore be positioned as an antecedent of perceived ease of use. When a platform is stable, responsive, and logically structured, students are more likely to perceive its operation as requiring limited effort. This relationship is consistent with the findings of Alkhawaja et al. [39], who identified technology-related perceptions as mechanisms through which system quality influenced e-learning acceptance.

Information quality refers to the characteristics of learning content and academic information provided through an e-learning system. It encompasses accuracy, relevance, completeness, clarity, organization, timeliness, and usefulness [5], [6], [22]. This construct is theoretically distinct from system quality because it concerns the substantive value of information rather than the technical conditions of delivery. Incomplete, outdated, ambiguous, or poorly organized information may reduce students' assessment of a platform's academic utility. Information quality is therefore positioned as an antecedent of perceived usefulness. Alkhuwaylidee [44] found that content quality contributed to perceived usefulness and confirmation, whereas Alotaibi and Alshahrani [40] identified information quality as a determinant of e-learning platform success.

User satisfaction constitutes an evaluative dimension of ISSM because it reflects users' overall assessment of their experience with an information system. In e-learning contexts, satisfaction may be formed through evaluations of system reliability, information usefulness, interaction effort, content quality, and support for learning activities [2], [5], [29]. Previous studies have associated system quality and information quality with user satisfaction and continued use in digital learning environments [23], [24], [26]. ISSM consequently provides a theoretical basis for examining how technical and informational attributes influence students' evaluations of e-learning systems.

2.4. Integrating TAM and ISSM in E-Learning Research

The integration of TAM and ISSM is theoretically justified because the two models explain complementary dimensions of e-learning use. TAM specifies how users form perceptions of usefulness and ease of use, whereas ISSM identifies the technical and informational attributes associated with system success, user experience, and satisfaction [2], [11], [22]. E-learning continuance cannot be explained solely through users' cognitive perceptions or system quality characteristics. Continued use is more plausibly understood as a process through which technical and informational quality attributes are translated into favorable technology perceptions and satisfactory prior experiences.

Prior research supports the integration of TAM and ISSM in educational technology contexts. Al-Fraihat et al. [2] developed a multidimensional model of e-learning system success that incorporated quality factors, learner perceptions, satisfaction, and perceived benefits. Al-Adwan et al. [1] found that sustainable e-learning success required consideration of system quality, perceived usefulness, satisfaction, and learning-related outcomes. Legramante et al. [11] applied an integrated TAM–ISSM perspective to Moodle use and identified relationships among information quality, perceived ease of use, perceived usefulness, satisfaction, and continuity of use. AL-Hawamleh [34] similarly demonstrated the relevance of combining ISSM and TAM when explaining satisfaction and continuance intention. Collectively, these studies support the application of an integrated model to post-adoption e-learning behavior.

The proposed framework positions system quality and information quality as external antecedents of perceived ease of use and perceived usefulness. System quality represents the technical dimension of ISSM. Reliable access, system responsiveness, interface consistency, and efficient navigation are expected to reduce the effort required to operate the platform and improve its perceived academic utility. Information quality represents the informational dimension of ISSM. Accurate, relevant, complete, understandable, and logically organized content is expected to increase the platform's perceived usefulness and reduce the cognitive effort required to locate and interpret academic information.

Perceived usefulness and perceived ease of use represent the cognitive evaluation component derived from TAM. User satisfaction is positioned as an evaluative response formed through prior system experience, whereas continuance intention represents the post-adoption behavioral outcome. The proposed sequence assumes that positive assessments of technical performance and information quality contribute to favorable technology perceptions, which subsequently shape satisfaction and intention to continue using the system. Buabeng-Andoh [50] found that satisfaction exerted the strongest influence on continuous intention to use a mobile learning management system. Dai et al. [51] similarly identified satisfaction and perceived usefulness as major predictors of learners' continuance intention toward online education platforms.

2.5. User Satisfaction and Continuance Intention in E-Learning Systems

User satisfaction has been established as a central construct in information systems and consumer behavior research. Oliver [25] conceptualized satisfaction as an evaluative response derived from the comparison between prior expectations and actual experience. Within information systems research, satisfaction is commonly treated as an outcome of system quality, information quality, and user perceptions, as well as an antecedent of continued use [8], [22], [28]. In e-learning contexts, satisfaction reflects students' overall assessment of system usefulness, ease of operation, content quality, technical reliability, and support for academic activities [2], [5], [29].

Continuance intention refers to the intention to maintain system use after initial adoption and direct experience. This construct is analytically distinct from initial acceptance because users may begin using an e-learning platform because of institutional requirements rather than voluntary preference. Continued use is more closely associated with satisfaction, perceived usefulness, and confirmation of the system's value [8], [9], [12]. Meta-analytic evidence indicates that satisfaction and perceived usefulness are among the strongest predictors of continuance intention toward online education platforms [9]. Studies of e-learning systems have also identified satisfaction as a mediating mechanism between technology-related perceptions and continuance intention [5], [11], [34].

The theoretical specification of satisfaction as an immediate antecedent of continuance intention is consistent with post-adoption behavior theory. Continued use is based on accumulated experience rather than platform availability alone. Students are more likely to maintain system use when prior interactions confirm that the platform is useful, operationally manageable, technically reliable, and relevant to academic requirements [8], [25]. Pan et al. [52] associated learners' post-use evaluations with continued use of online education platforms. Huang [53] further reported that perceived usefulness and perceived enjoyment mediated the relationship between confirmation and continuance intention in asynchronous online learning.

In the proposed model, satisfaction functions as the evaluative mechanism connecting perceived usefulness and perceived ease of use with continuance intention. Perceived usefulness is expected to increase satisfaction when students assess that the system supports academic performance, task completion, communication, and learning efficiency. Perceived ease of use is expected to increase satisfaction when intuitive navigation and limited operational complexity reduce the effort required to complete learning activities. Satisfaction subsequently represents students' consolidated evaluation of prior system use and is expected to predict their intention to continue using the e-learning platform.

2.6. Proposed Research Model

Integrating TAM and ISSM, the proposed model positions system quality and information quality as antecedents of perceived ease of use and perceived usefulness. These perceptions influence user satisfaction, which subsequently determines continuance intention. Thus, e-learning continuance is explained through sequential relationships among system quality, user perceptions, satisfaction, and post-adoption intention.

The proposed model explains how quality factors influence continuance intention. System quality and information quality, derived from ISSM, serve as external antecedents. Perceived usefulness and perceived ease of use, derived from TAM, represent cognitive beliefs. User satisfaction reflects post-use evaluation, while continuance intention represents post-adoption behavioral intention. The model integrates these constructs into a single structural framework for empirical evaluation.

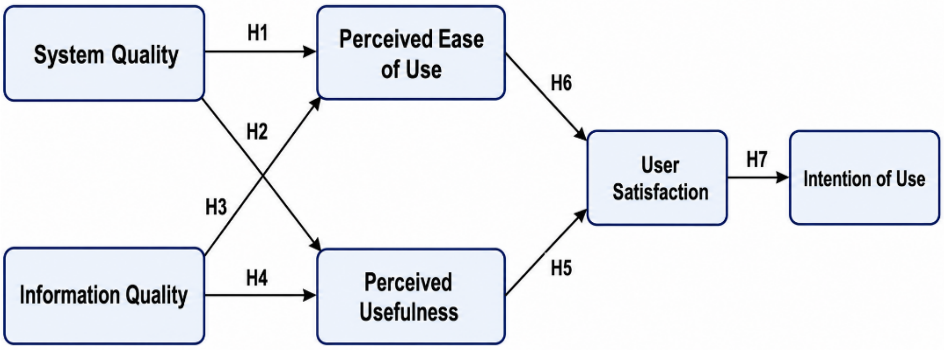

Figure 1. Proposed theoretical model and hypotheses.

2.7. Hypothesis Development

2.7.1. System Quality, Perceived Ease of Use, and Perceived Usefulness

System quality refers to the technical performance and functional characteristics of an information system, including reliability, accessibility, response speed, stability, interface quality, and navigation efficiency [6], [22], [23]. In e-learning environments, high system quality enables students to access learning materials, navigate course pages, and interact with platform functions without substantial technical difficulty. Stable system performance, responsive interfaces, and coherent navigation structures reduce operational effort and are therefore expected to strengthen perceived ease of use [54], [55].

System quality may also shape perceived usefulness because reliable technical performance supports students in completing academic tasks, accessing instructional resources, and managing learning activities efficiently. Technical disruptions, delayed responses, and inconsistent functionality may reduce the academic value attributed to the platform. When these barriers are limited, students are more likely to evaluate the system as beneficial for learning performance [24], [26]. Previous studies have associated system quality with perceived usefulness and users' evaluations of e-learning systems [11], [23]. Based on this theoretical and empirical reasoning, the following hypotheses are proposed:

H1: System quality has a positive effect on the perceived ease of use of e-learning systems.
H2: System quality has a positive effect on the perceived usefulness of e-learning systems.

2.7.2. Information Quality, Perceived Ease of Use, and Perceived Usefulness

Information quality refers to the extent to which information provided through a system is accurate, relevant, complete, timely, understandable, well organized, and appropriate to users' requirements [22], [28]. Within e-learning systems, information quality is reflected in the clarity of instructional materials, relevance of course content, completeness of academic information, logical organization of learning resources, and correspondence between the information provided and students' learning requirements [2], [5], [6]. High-quality information supports students in interpreting course requirements, completing assignments, following instructional procedures, and achieving learning objectives.

Information quality is expected to influence perceived usefulness because the academic value of an e-learning platform depends substantially on the quality of the content it provides. Relevant, accurate, and meaningful instructional information can strengthen students' assessment that the system supports learning effectiveness and academic performance [23], [24]. Information quality may also influence perceived ease of use. Clearly structured and consistently presented information can reduce cognitive effort, minimize ambiguity, and facilitate the retrieval of learning resources. A coherent information environment may therefore cause the platform to be perceived as easier to use, even when its technical functions remain unchanged [2], [5].

Previous studies have associated information accuracy, relevance, completeness, clarity, and timeliness with perceived usefulness, perceived ease of use, satisfaction, and continuance intention [56], [57]. In the proposed model, information quality is therefore expected to shape both students' assessments of operational effort and their evaluations of the platform's academic value. The following hypotheses are proposed:

H3: Information quality has a positive effect on the perceived ease of use of e-learning systems.
H4: Information quality has a positive effect on the perceived usefulness of e-learning systems.

2.7.3. Perceived Usefulness, Perceived Ease of Use, and User Satisfaction

Perceived usefulness is expected to influence satisfaction because users tend to evaluate a system more positively when it supports the achievement of relevant objectives [14], [15]. In e-learning contexts, students are more likely to report satisfaction when the system facilitates access to instructional materials, supports academic productivity, improves communication, and enables learning tasks to be completed efficiently [2], [16], [17]. The academic benefits attributed to the platform consequently provide a cognitive basis for satisfaction.

Perceived ease of use is also expected to influence satisfaction because operational simplicity shapes the quality of students' interaction with the system. A platform that is easy to learn, navigate, and operate can reduce confusion and unnecessary cognitive effort. When students can complete academic activities without substantial technical difficulty, they are more likely to evaluate the overall experience positively [5], [10], [14]. Previous e-learning studies have associated perceived ease of use with satisfaction because usability influences students' comfort, confidence, and willingness to interact with digital learning platforms [11], [29]. The following hypotheses are proposed:

H5: Perceived usefulness has a positive effect on user satisfaction with e-learning systems.
H6: Perceived ease of use has a positive effect on user satisfaction with e-learning systems.

2.7.4. User Satisfaction and Continuance Intention

User satisfaction reflects users' overall evaluation of their prior experience with an information system and is consistently positioned as a predictor of continuance intention [8], [22], [25]. In e-learning contexts, satisfied students are more likely to maintain system use because prior interaction has provided identifiable academic value, operational convenience, and support for learning activities [2], [5]. Satisfaction therefore represents an accumulated evaluation rather than an immediate response to a single system feature.

Continuance intention is particularly relevant in higher education because initial platform use may result from institutional requirements, whereas sustained use depends more directly on students' satisfaction and perceived benefits. Previous studies have consistently associated satisfaction with continuance intention in e-learning and online education environments [9], [11], [12], [34]. Students who evaluate system performance, information quality, usefulness, and ease of use positively are more likely to intend to use the platform in subsequent academic activities. The following hypothesis is proposed:

H7: User satisfaction has a positive effect on continuance intention to use e-learning systems.

3. MATERIALS AND METHODS

3.1. Research Design and Theoretical Positioning

This study employed a quantitative explanatory survey design with a cross-sectional data-collection approach. The explanatory design was selected because the study examined theoretically specified relationships among latent variables rather than restricting the analysis to a descriptive assessment of students' perceptions of e-learning systems. Data were collected at a single point in time from university students with prior experience using institutional e-learning platforms.

The proposed research model integrated the Technology Acceptance Model and the Information Systems Success Model. System quality and information quality were specified as external quality-related antecedents derived from the Information Systems Success Model. Perceived ease of use and perceived usefulness represented technology-related cognitive evaluations derived from the Technology Acceptance Model. User satisfaction was positioned as an evaluative response to prior system use, whereas continuance intention represented the post-adoption intention to maintain future use of the e-learning system.

Covariance-based structural equation modeling was applied to evaluate the proposed model. CB-SEM was considered appropriate because the analysis was directed toward theory testing, model confirmation, and simultaneous estimation of relationships among multiple latent constructs [58]–[60]. The analytical procedure comprised two sequential stages: evaluation of the measurement model and evaluation of the structural model. The measurement model was assessed before the hypothesized structural relationships were interpreted.

3.2. Data Source and Relationship to the Previous Publication

The study used a cross-sectional survey dataset previously analyzed by Fitria et al. [35]. The dataset contained 470 valid responses from students enrolled at five Indonesian universities who had experience using institutional e-learning systems. The empirical sample was reused to examine a theoretical specification that differed from the model evaluated in the previous publication.

The previous study examined the relationship between system quality and user satisfaction through perceived ease of use and perceived usefulness. The present study extended that analytical scope by incorporating information quality and continuance intention into an integrated TAM–ISSM model. The current analysis therefore differed in its theoretical framing, construct configuration, hypothesis structure, and dependent outcome. Continuance intention, rather than user satisfaction alone, was specified as the final post-adoption outcome.

Reuse of the dataset did not involve the collection of additional responses or the alteration of the original observations. The analysis was conducted using a distinct research objective and structural model. This distinction was reported to clarify the relationship between the present study and the previous publication and to prevent ambiguity regarding the origin of the empirical data.

3.3. Empirical Context

The empirical context was the use of institutional e-learning systems in higher education. These systems were used to support academic activities, including access to learning materials, course-related communication, assignment submission, feedback delivery, and learning-information management. E-learning was therefore conceptualized as both a technological platform and an academic information environment through which students accessed, processed, and exchanged learning-related resources.

Respondents were drawn from five institutions: Universitas Negeri Makassar, Universitas Hasanuddin, Universitas Muhammadiyah Makassar, Universitas Negeri Malang, and Universitas Islam Negeri Makassar. The inclusion of multiple universities provided institutional variation within the dataset and enabled the proposed model to be examined across students from different academic settings.

The analytical focus remained at the individual level. Institutional differences were not modeled as contextual effects, grouping variables, or moderators. Consequently, the multi-university composition of the sample provided broader empirical coverage but did not constitute a formal comparison among universities.

3.4. Population, Eligibility and Sampling Procedure

The target population consisted of university students who had used institutional e-learning systems for academic purposes. The unit of analysis was the individual student as an active user of an e-learning platform.

Respondents were eligible for inclusion when they met three criteria. First, the respondent was registered as an active university student. Second, the respondent had used an institutional e-learning system. Third, the respondent had sufficient usage experience to evaluate system quality, information quality, perceived ease of use, perceived usefulness, user satisfaction, and continuance intention.

Purposive sampling was applied because the constructs required evaluations based on direct experience with e-learning systems. Students without prior system-use experience could not provide substantively valid responses concerning the technical quality, information quality, usability, usefulness, satisfaction, or intended continued use of the platform.

A total of 470 valid responses were retained for analysis. The sample size was considered adequate for covariance-based structural equation modeling because it provided sufficient observations for the estimation of the latent-variable model and exceeded commonly recommended minimum requirements for models containing multiple constructs and observed indicators [59], [60]. An adequate sample is required in CB-SEM to support stable parameter estimation, goodness-of-fit evaluation, and interpretation of structural coefficients.

Because purposive sampling is a non-probability sampling procedure, population representativeness cannot be assumed. The findings should therefore be generalized cautiously and are most directly applicable to students with e-learning experience in institutional contexts comparable to those represented in the sample.

3.5. Construct Operationalization and Measurement Items

The research instrument measured six latent constructs: system quality, information quality, perceived ease of use, perceived usefulness, user satisfaction, and continuance intention. The constructs were operationalized using measurement items adapted from established studies on technology acceptance, information-system success, post-adoption behavior, and e-learning evaluation.

System quality represented students' evaluations of the technical and functional performance of the e-learning system. The construct included system structure, operational ease, reliability, responsiveness, and interactive functionality.

Information quality represented students' evaluations of the characteristics of the learning information delivered through the platform. The construct covered comprehensiveness, organization, relevance to learning needs, correspondence with user expectations, accuracy, and currency of information.

Perceived ease of use represented the degree to which students considered the e-learning system accessible, understandable, learnable, navigable, and operationally uncomplicated. Perceived usefulness represented the degree to which students considered the system beneficial for saving time, increasing knowledge, delivering learning materials, and supporting learning efficiency.

User satisfaction represented students' evaluative response to their experience with the e-learning system. Continuance intention represented students' stated intention to maintain use of the system in future learning activities. The measurement items and their principal sources are presented in Table 1.

Table 1. Measurement items and sources.

Construct	Code	Measurement item	Sources
System Quality	SYQ1	The e-learning system has a well-structured and understandable design.	[22]; [6]
	SYQ2	The e-learning system is easy to operate.	[22]; [5]
	SYQ3	The e-learning system is reliable and rarely experiences disruptions.	[22]; [23]

Construct	Code	Measurement item	Sources
	SYQ4	The e-learning system responds quickly during use.	[22]; [2]
	SYQ5	The e-learning system provides interactive features that support user engagement.	[5]; [2]
Information Quality	INQ1	The e-learning system provides comprehensive learning information.	[22]; [6]
	INQ2	The learning content is organized effectively.	[5]; [2]
	INQ3	The information provided meets my learning needs.	[22]; [23]
	INQ4	The information provided aligns with my expectations.	[6]; [2]
	INQ5	The learning information provided through the e-learning system is accurate, relevant, and up to date.	[22]
Perceived Ease of Use	PEU1	Accessing the e-learning system across devices is easy.	[14]; [15]
	PEU2	Learning to use the e-learning system is easy.	[14]
	PEU3	The e-learning system is user-friendly.	[14]; [5]
	PEU4	Navigation in the e-learning system is easy to learn.	[14]; [17]
	PEU5	Using the e-learning system feels comfortable and straightforward.	[14]; [10]
Perceived Usefulness	POU1	The e-learning system saves time in learning activities.	[14]
	POU2	The e-learning system enhances my knowledge.	[14]; [23]
	POU3	The e-learning system effectively delivers learning materials.	[14]; [2]
	POU4	The e-learning system supports learning efficiency.	[14]
User Satisfaction	USA1	I am satisfied with access to additional learning materials through the system.	[5]; [22]
	USA2	I am satisfied with my experience using the e-learning system.	[5]; [2]
	USA3	The e-learning system provides useful feedback on my learning progress.	[5]
Continuance Intention	CUI1	I intend to use the e-learning system in the long term.	[8]
	CUI2	I intend to continue using the e-learning system for future learning activities.	[8]; [10]
	CUI3	I plan to continue using the e-learning system as part of my learning activities.	[8]; [12]

The measurement items were adapted to the institutional e-learning context while retaining their underlying theoretical meanings. Previously established items were used to support construct representation and theoretical correspondence with the integrated TAM–ISSM model. The use of adapted indicators does not independently establish validity; the statistical adequacy of the items was subsequently evaluated through the measurement-model assessment.

3.6. Response Scale and Instrument Administration

All measurement items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This response format was applied consistently across the six latent constructs: system quality, information quality, perceived ease of use, perceived usefulness, user satisfaction, and continuance intention. Higher scores indicated stronger respondent agreement with the statements representing each construct.

The five-point scale was used to quantify respondents' evaluations of their experiences with institutional e-learning systems while maintaining a uniform response structure across all measurement items. The same scale specification was retained in the questionnaire, data coding procedure, descriptive analysis, measurement-model evaluation, and structural-model estimation.

Instrument adaptation procedures should be reported only when they were actually performed. When the items were translated from English into Indonesian, the methodological description should specify the translation procedure, independent back-translation, expert evaluation, and any pilot assessment used to examine semantic equivalence and respondent comprehension [59], [61]. These procedures should not be claimed without documentary evidence from the original data-collection process.

3.7. Data Analysis Procedure

Data analysis was conducted using IBM SPSS Statistics and IBM SPSS AMOS. SPSS was used for data screening, respondent-profile analysis, descriptive statistical procedures, and preliminary diagnostics. AMOS was used to estimate the measurement and structural models through covariance-based structural equation modeling.

The analytical procedure was implemented sequentially. The measurement model was first evaluated to determine whether the observed indicators represented their respective latent constructs with adequate reliability and validity. Structural-path estimation was conducted only after the measurement model satisfied the specified assessment criteria.

The measurement-model evaluation included standardized factor loadings, Cronbach's alpha, composite reliability, average variance extracted, the

Fornell–Larcker criterion, and the heterotrait–monotrait ratio of correlations. These statistics were used to assess indicator reliability, internal consistency, convergent validity, and discriminant validity.

Indicator reliability was evaluated using standardized factor loadings. Loadings of at least 0.70 were preferred, although values of at least 0.50 may be retained when supported by adequate construct reliability and theoretical justification [59], [60]. Internal consistency was assessed using Cronbach's alpha and composite reliability, with values of at least 0.70 interpreted as acceptable [59].

Convergent validity was assessed using average variance extracted. An AVE value of at least 0.50 indicates that the construct explains at least half of the variance in its observed indicators [62]. Discriminant validity was evaluated using the Fornell–Larcker criterion and HTMT. Under the Fornell–Larcker criterion, the square root of the AVE for each construct should exceed its correlations with other constructs [62]. HTMT values below 0.85 were interpreted as satisfying the conservative discriminant-validity threshold, while values below 0.90 may be accepted under less restrictive conditions [63]. The measurement-model criteria are summarized in Table 2.

Table 2. Criteria for measurement-model evaluation.

Assessment area	Indicator	Recommended criterion	Reference
Indicator reliability	Standardized factor loading	≥ 0.70 preferred; ≥ 0.50 conditionally acceptable	[59], [60]
Internal consistency	Cronbach's alpha	≥ 0.70	[59]
Internal consistency	Composite reliability	≥ 0.70	[59]
Convergent validity	Average variance extracted	≥ 0.50	[62]
Discriminant validity	Fornell–Larcker criterion	Square root of AVE exceeds inter-construct correlations	[62]
Discriminant validity	HTMT	< 0.85; < 0.90 under less conservative criteria	[63]

After measurement adequacy was established, the structural model was evaluated by estimating the hypothesized direct relationships among the six constructs. Structural-path interpretation was based on the direction and magnitude of standardized regression coefficients, critical ratios, and p-values. A two-tailed significance level of 0.05 was applied. Critical-ratio values with an absolute magnitude greater than approximately 1.96 were interpreted as statistically significant [59], [60].

The reported analysis did not apply bootstrapping and did not formally estimate indirect effects. The structural interpretation was therefore restricted to the direct paths specified in the research hypotheses. Mediation should not be inferred solely from a sequence of statistically significant direct relationships.

3.8. Model-Fit Evaluation and Model Modification

Model adequacy was evaluated using multiple goodness-of-fit indices. A multi-index assessment was applied because a single fit statistic does not provide sufficient evidence to determine whether a covariance structure adequately represents the observed data [59], [60], [64].

The evaluated indices included the chi-square divided by degrees of freedom ratio, goodness-of-fit index, adjusted goodness-of-fit index, normed fit index, incremental fit index, Tucker–Lewis index, comparative fit index, root mean square error of approximation, parsimony normed fit index, and parsimony comparative fit index.

CMIN/DF values below 3.00 were interpreted as indicating acceptable relative fit. GFI, AGFI, NFI, IFI, TLI, and CFI values of at least 0.90 were interpreted as acceptable, while values approaching or exceeding 0.95 represented stronger fit for selected incremental indices [59], [60], [64], [65]. RMSEA values below 0.08 indicated acceptable approximation error, whereas values below 0.06 indicated closer fit [60], [64]. PNFI and PCFI values above 0.50 were interpreted as acceptable evidence of parsimonious fit [64], [66]. The model-fit criteria are presented in Table 3.

Table 3. Model-fit index criteria for CB-SEM

Fit index	Recommended criterion	Interpretation	References
CMIN/DF	< 3.00	Acceptable relative fit	[59], [60]
GFI	≥ 0.90	Acceptable absolute fit	[59]
AGFI	≥ 0.90	Acceptable adjusted absolute fit	[59]
NFI	≥ 0.90	Acceptable incremental fit	[59], [64]
IFI	≥ 0.90; ≥ 0.95 preferred	Acceptable incremental fit	[65]
TLI	≥ 0.90; ≥ 0.95 preferred	Acceptable incremental fit	[64]
CFI	≥ 0.90; ≥ 0.95 preferred	Acceptable incremental fit	[64]
RMSEA	< 0.08; < 0.06 preferred	Acceptable approximation error	[60], [64]

Fit index	Recommended criterion	Interpretation	References
PNFI	> 0.50	Acceptable parsimonious fit	[64], [66]
PCFI	> 0.50	Acceptable parsimonious fit	[64], [66]

Model modification was conducted only when the initial model failed to meet the specified fit criteria. Modification indices and standardized residuals were used as diagnostic evidence, while residual covariances were added only when supported by a defensible conceptual or measurement-related basis.

The modified model was evaluated using the same fit indices and retained when statistical fit improved without altering the core theoretical relationships. Because data-driven modifications may produce sample-specific results, the final model should be interpreted cautiously and validated using an independent sample.

4. RESULTS

4.1. Respondent Characteristics

The demographic composition of the sample was examined according to gender, age, and university affiliation. These characteristics were reported to describe the distribution of respondents across relevant demographic and institutional categories. Because no subgroup comparison was conducted in this section, the demographic data should be interpreted as descriptive information rather than evidence of differences in perceptions or e-learning behavior.

Table 4. Demographic characteristics of the respondents.

Category	Classification	Frequency (n = 470)	Percentage (%)
Gender	Male	164	34.89
	Female	306	65.11
Age	18 years	70	14.89
	19 years	85	18.09
	20 years	100	21.28
	21 years	90	19.15
	22 years	75	15.96
	23 years	50	10.64
University	Universitas Negeri Makassar	118	25.11
	Universitas Hasanuddin	94	20.00
	Universitas Muhammadiyah Makassar	71	15.11
	Universitas Negeri Malang	101	21.49
	Universitas Islam Negeri Makassar	86	18.30

As shown in Table 4, female respondents comprised 65.11% of the sample, while male respondents represented 34.89%. Most respondents were aged 19–21 years, accounting for 58.52% of the sample, with those aged 20 years forming the largest age group at 21.28%.

Universitas Negeri Makassar contributed the largest proportion of respondents at 25.11%, followed by Universitas Negeri Malang at 21.49%, Universitas Hasanuddin at 20.00%, Universitas Islam Negeri Makassar at 18.30%, and Universitas Muhammadiyah Makassar at 15.11%. Together, Universitas Negeri Makassar and Universitas Negeri Malang represented 46.60% of the sample.

4.2. Measurement Model Evaluation

The reflective measurement model was evaluated using standardized factor loadings, Cronbach's alpha, composite reliability, and average variance extracted. Standardized factor loadings of at least 0.70 indicate adequate indicator reliability, while Cronbach's alpha and composite reliability values above 0.70 indicate acceptable internal consistency. An average variance extracted value above 0.50 indicates that a construct explains more than half of the variance in its indicators, thereby supporting convergent validity [67]–[69].

Table 5. Results of the reliability and convergent-validity assessment.

Construct	Indicator	Standardized Factor Loading	Cronbach's Alpha	C.R.	AVE
System Quality	SYQ1	0.726	0.905	0.904	0.654
	SYQ2	0.821			
	SYQ3	0.889			

Construct	Indicator	Standardized Factor Loading	Cronbach's Alpha	C.R.	AVE
	SYQ4	0.799			
	SYQ5	0.799			
Information Quality	INQ1	0.870	0.908	0.919	0.694
	INQ2	0.740			
	INQ3	0.873			
	INQ4	0.890			
	INQ5	0.783			
Perceived Ease of Use	PEU1	0.709	0.917	0.925	0.715
	PEU2	0.863			
	PEU3	0.921			
	PEU4	0.897			
	PEU5	0.820			
Perceived Usefulness	POU1	0.849	0.908	0.894	0.679
	POU2	0.796			
	POU3	0.898			
	POU4	0.744			
User Satisfaction	SAT1	0.769	0.913	0.872	0.695
	SAT2	0.877			
	SAT3	0.851			
Continuance Intention	CI1	0.763	0.903	0.825	0.612
	CI2	0.718			
	CI3	0.859			

The standardized factor loadings ranged from 0.709 to 0.921. The lowest loading was recorded for PEU1, whereas the highest loading was recorded for PEU3. All indicators exceeded the recommended minimum loading of 0.70 and were therefore retained in the measurement model.

Cronbach's alpha values ranged from 0.903 to 0.917, while composite reliability values ranged from 0.825 to 0.925. Each construct exceeded the recommended reliability threshold of 0.70, indicating adequate internal consistency. The average variance extracted values ranged from 0.612 to 0.715 and exceeded the minimum criterion of 0.50. These results support the indicator reliability, internal consistency, and convergent validity of the six latent constructs [70], [71].

Discriminant validity was initially evaluated using the Fornell–Larcker criterion. Under this criterion, the square root of the average variance extracted for each construct should exceed the construct's correlations with all other constructs in the model.

Table 6. Fornell–Larcker discriminant-validity assessment.

Construct	SYQ	INQ	PEU	POU	SAT	CI
System Quality (SYQ)	**0.809**					
Information Quality (INQ)	0.625	**0.833**				
Perceived Ease of Use (PEU)	0.442	0.778	**0.846**			
Perceived Usefulness (POU)	0.037	0.219	0.625	**0.824**		
User Satisfaction (SAT)	0.319	0.374	0.479	0.298	**0.834**	
Continuance Intention (CI)	0.195	0.229	0.293	−0.012	0.608	**0.782**

The square roots of the average variance extracted, presented in bold on the diagonal of Table 6, ranged from 0.782 for continuance intention to 0.846 for perceived ease of use. Each diagonal value exceeded the corresponding inter-construct correlations. The largest correlation was observed between information quality and perceived ease of use ($r = 0.778$).

This value remained below the square roots of the average variance extracted for information quality (0.833) and perceived ease of use (0.846). The Fornell–Larcker criterion was therefore satisfied for all constructs. Discriminant validity was also evaluated using the heterotrait–monotrait ratio of correlations. Figure 2 presents the HTMT values for the six latent constructs.

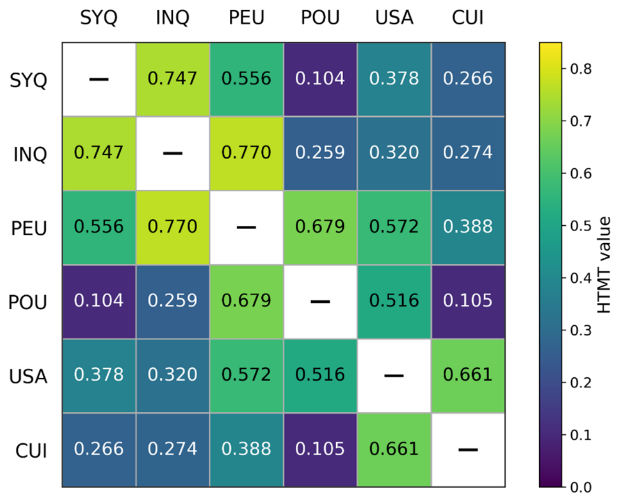

Figure 2. Heatmap of the Heterotrait–monotrait (HTMT) ratio of correlations.

The HTMT values ranged from 0.104 to 0.770 and remained below the conservative threshold of 0.85 [63]. The largest HTMT ratio was observed between information quality and perceived ease of use (HTMT = 0.770), followed by perceived ease of use and perceived usefulness (HTMT = 0.679) and user satisfaction and continuance intention (HTMT = 0.661). These findings indicate that the latent constructs were empirically distinguishable under the HTMT criterion. No discriminant-validity problem was identified based on either the Fornell–Larcker criterion or the HTMT assessment.

4.3. Model Fit Before and After Modification

Model fit was evaluated before and after model modification using absolute, incremental, and parsimonious fit indices. The assessment applied the recommended criteria of CMIN/DF below 3.00, GFI, AGFI, NFI, IFI, TLI, and CFI values of at least 0.90, RMSEA below 0.08, and PNFI and PCFI values above 0.50 [64], [72].

Table 7. Comparison of model-fit indices before and after model modification.

Fit Index	Threshold	Initial	Final	Interpretation
CMIN/DF	< 3.00	4.788	1.036	Acceptable
GFI	≥ 0.90	0.803	0.963	Acceptable
AGFI	≥ 0.90	0.760	0.945	Acceptable
NFI	≥ 0.90	0.829	0.969	Acceptable
IFI	≥ 0.90	0.859	0.999	Acceptable
TLI	≥ 0.90	0.841	0.999	Acceptable
CFI	≥ 0.90	0.859	0.999	Acceptable
RMSEA	< 0.08	0.091	0.009	Acceptable
PNFI	> 0.50	0.737	0.714	Acceptable
PCFI	> 0.50	0.764	0.736	Acceptable

The initial model did not demonstrate adequate overall fit. The CMIN/DF value of 4.788 exceeded the recommended maximum of 3.00, while the RMSEA value of 0.091 exceeded the recommended upper limit of 0.08. The GFI, AGFI, NFI, IFI, TLI, and CFI values were also below 0.90. Although the PNFI and PCFI values satisfied their respective thresholds, the collective evidence indicated inadequate fit for the initial model.

Following model modification, the CMIN/DF value decreased from 4.788 to 1.036, and the RMSEA value decreased from 0.091 to 0.009. The GFI, AGFI, NFI, IFI, TLI, and CFI values increased above the recommended threshold of 0.90. The PNFI and PCFI values declined from 0.737 to 0.714 and from 0.764 to 0.736, respectively, but remained above the minimum value of 0.50. Taken together, the final model satisfied the specified absolute, incremental, and parsimonious fit criteria.

Figure 3 compares the initial and modified models. The modification procedure introduced covariance relationships among selected residual terms while retaining the hypothesized structural relationships among the latent constructs. These modifications were associated with improved model-fit indices.

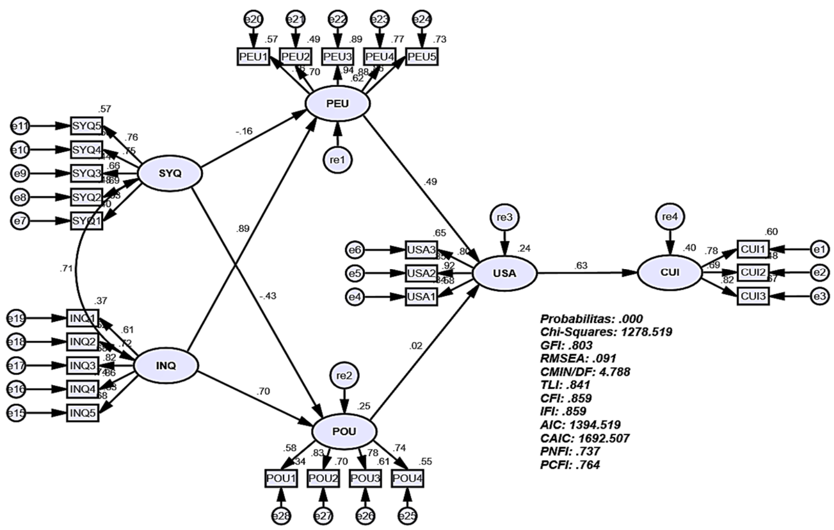

Figure 3. Initial research model (before modification)

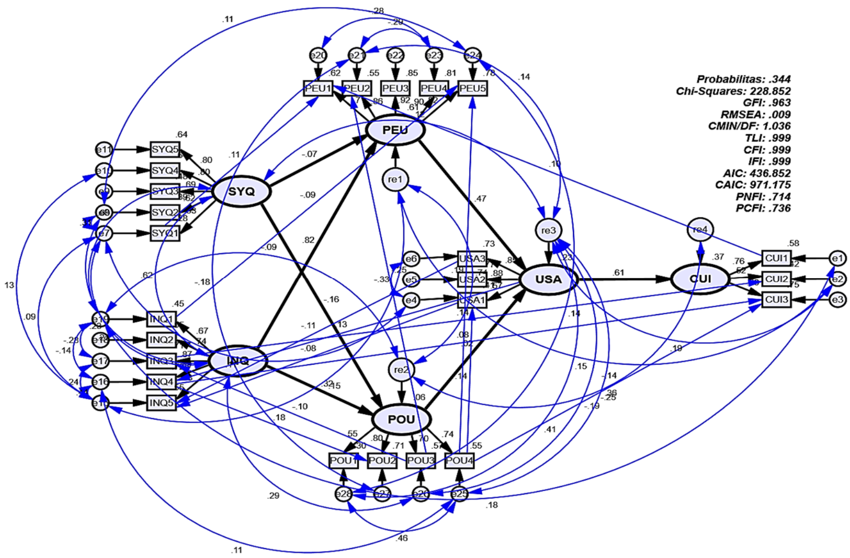

Figure 4. Final research model (after modification)

The improved fit indicates that the modified covariance structure represented the observed data more adequately than the initial specification. Nevertheless, covariance relationships among residual terms should be supported by substantive or measurement-based justification rather than statistical modification indices alone. This consideration is relevant because data-driven modifications may reflect sample-specific characteristics and can reduce the generalizability of the fitted model.

4.4. Structural Model and Hypothesis Testing

The structural model evaluated seven direct relationships among system quality, information quality, perceived ease of use, perceived usefulness, user satisfaction, and continuance intention. Hypothesis testing was based on the critical ratio, p-value, and standardized regression coefficient. For a two-tailed test ($\alpha = 0.05$), a critical ratio with an absolute value greater than approximately 1.96 was interpreted as statistically significant [60].

Bootstrapping was not applied, and indirect effects were not formally estimated. The analysis was therefore restricted to the direct structural paths specified in H1–H7. No conclusions regarding mediation were derived from the reported results.

Table 8. Direct structural-path results.

Hypothesis	Structural Path			CR	p-value	β	Decision	Interpretation
H1	SYQ	→	PEU	2.094	0.036	0.164	Supported	Positive and statistically significant
H2	SYQ	→	POU	2.340	0.019	0.072	Supported	Positive and statistically significant
H3	INQ	→	PEU	3.803	< 0.001	0.321	Supported	Positive and statistically significant
H4	INQ	→	POU	11.633	< 0.001	0.824	Supported	Positive and statistically significant
H5	POU	→	SAT	6.463	< 0.001	0.475	Supported	Positive and statistically significant
H6	PEU	→	SAT	2.195	0.028	0.019	Statistically supported	Positive but substantively negligible
H7	SAT	→	CI	8.229	< 0.001	0.612	Supported	Positive and statistically significant

In Table 8, all seven direct paths were statistically significant at the 5% level. Information quality had the largest standardized association with perceived usefulness ($\beta = 0.824$, $p < 0.001$). User satisfaction was positively associated with continuance intention ($\beta = 0.612$, $p < 0.001$). This coefficient was the second largest in the structural model and indicates that higher satisfaction was associated with a stronger intention to continue using the e-learning system. Perceived usefulness also had a positive association with user satisfaction ($\beta = 0.475$, $p < 0.001$). Information quality was positively associated with perceived ease of use ($\beta = 0.321$, $p < 0.001$). By comparison, system quality had smaller positive associations with perceived ease of use ($\beta = 0.164$, $p = 0.036$) and perceived usefulness ($\beta = 0.072$, $p = 0.019$).

The path from perceived ease of use to user satisfaction was statistically significant ($\beta = 0.019$, $p = 0.028$). However, the standardized coefficient was close to zero, indicating negligible substantive magnitude. H6 was therefore supported in a statistical sense, but the result should not be interpreted as evidence of a practically meaningful relationship. The distinction between statistical significance and substantive relevance is particularly necessary in this case because the sample size may permit the detection of effects that have limited practical importance.

5. DISCUSSION

This study integrated the Information Systems Success Model and the Technology Acceptance Model to explain students' continuance intention toward institutional e-learning systems. All seven hypotheses were statistically supported, although the magnitude of the estimated relationships differed substantially. Information quality exerted the strongest effect on perceived usefulness (H4: $\beta = 0.824$, $p < 0.001$) and a moderate effect on perceived ease of use (H3: $\beta = 0.321$, $p < 0.001$). User satisfaction strongly predicted continuance intention (H7: $\beta = 0.612$, $p < 0.001$), whereas perceived usefulness had a moderate effect on satisfaction (H5: $\beta = 0.475$, $p < 0.001$). By contrast, system quality had weak effects on perceived ease of use (H1: $\beta = 0.164$, $p = 0.036$) and perceived usefulness (H2: $\beta = 0.072$, $p = 0.019$). Perceived ease of use also had a statistically significant but substantively negligible effect on satisfaction (H6: $\beta = 0.019$, $p = 0.028$).

The overall pattern indicates that sustained e-learning use was more strongly associated with the academic value of the information provided and students' cumulative satisfaction than with technical functionality alone. This interpretation is consistent with post-adoption research showing that continuance decisions are primarily shaped by experienced usefulness and satisfaction after direct system use [18], [73], [74]. Meta-analytic evidence has similarly identified satisfaction and perceived usefulness as central determinants of information technology continuance, although the magnitude of these relationships varies across empirical contexts [75]. Because the present study used a cross-sectional design, applied a respecified final model, and did not estimate indirect effects, the reported relationships should be interpreted as structural associations rather than causal or mediating mechanisms.

5.1. Effects of System Quality on Perceived Ease of Use and Perceived Usefulness

System quality was positively associated with perceived ease of use and perceived usefulness, thereby supporting H1 and H2. Reliable access, responsive system performance, coherent interface design, and efficient navigation can reduce operational barriers and facilitate the completion of academic activities. This interpretation is consistent with evidence indicating that the technical performance of an e-learning environment contributes to students' evaluations of digital learning services. Pham et al. [76], for example, identified system quality as a major component of overall e-learning service quality, which subsequently influenced student satisfaction and loyalty. Subsequent evaluations of e-learning system success have also confirmed that technical quality remains a relevant component of post-pandemic digital learning environments [55], [77]–[79].

The small path coefficients nevertheless indicate that system quality explained only a limited proportion of variation in perceived ease of use and perceived usefulness. As institutional e-learning systems become routinely used, reliability, accessibility, response speed, and basic navigation may operate as minimum performance requirements rather than distinctive sources of academic value [73], [80]. Their presence may prevent dissatisfaction, but incremental improvements may produce only limited changes in students' perceptions after the platform has become familiar. At the post-adoption stage, user evaluations tend to shift toward experienced usefulness, satisfaction, and the perceived relevance of the learning environment [81].

Information quality may become more salient under these conditions because students evaluate whether the platform provides clear, relevant, current, and academically meaningful content [82], [83]. Continued use may also depend on engagement, interaction quality, pedagogical design, and institutional support [84], [85]. System quality therefore appears to function as a necessary enabling condition, but not as the principal source of perceived academic value in the present sample.

The weak effects of system quality differ from findings in which technical performance and usability were stronger predictors of satisfaction or loyalty. This variation does not necessarily indicate inconsistency across studies. Instead, it suggests that the explanatory importance of system quality is contingent on platform maturity, compulsory system use, prior digital experience, device availability, and technical support. In the present context, system quality appears to provide the operational foundation for e-learning use, whereas students' evaluations of value were more strongly associated with the academic information delivered through the platform.

5.2. Effects of Information Quality on Perceived Ease of Use and Perceived Usefulness

The strongest relationship in the structural model was observed between information quality and perceived usefulness, thereby supporting H4. Students were more likely to perceive the e-learning system as useful when learning materials, assignment instructions, announcements, and academic information were relevant, complete, clearly organized, and aligned with learning requirements. This result shifts the analytical emphasis from the platform as a technical application to the platform as an academic information environment. The perceived usefulness of an e-learning system is therefore derived not only from its technological functions but also from the quality of the instructional and intellectual resources delivered through those functions.

This interpretation is consistent with studies showing that accurate, relevant, complete, and systematically organized information improves students' evaluations of e-learning systems [56], [57], [86]. Information quality has also been associated with stronger perceptions of academic usefulness and value in digital learning platforms [87], [88]. In post-emergency learning contexts, high-quality course information has been linked to satisfaction and continuance intention [82]. Timely academic information and effective monitoring may further strengthen students' assessments of e-learning benefits [88], [89]. Evidence from blended-learning contexts similarly indicates that perceived value translates service and learning quality into student satisfaction [90]. Within Indonesian higher education, information quality and satisfaction have also been identified as determinants of continued e-learning use [91].

Information quality was also moderately associated with perceived ease of use, thereby supporting H3. This result indicates that perceived ease of use is influenced by informational and cognitive characteristics in addition to technical usability. A technically functional interface may still be perceived as difficult when course folders are inconsistently labeled, assignment instructions are ambiguous, deadlines are outdated, or learning materials are distributed across multiple locations. Conversely, coherent information architecture can reduce search effort, interpretive uncertainty, and unnecessary cognitive processing. Pham et al. [76] similarly identified logical page organization and structured information content as factors that facilitate navigation and improve e-learning evaluations.

The magnitude of the relationship between information quality and perceived usefulness requires methodological caution. A coefficient of $\beta = 0.824$ indicates a strong empirical association and may also reflect conceptual proximity between evaluations of information quality and judgments of academic usefulness. Future research should cross-validate this relationship using independent samples and compare alternative measurement models. Discriminant validity should also be examined to ensure that indicators of information quality remain empirically distinguishable from perceived usefulness, system quality, and related system attributes. Such procedures are necessary to determine whether the estimated coefficient represents a robust substantive relationship or is partly influenced by measurement specification.

5.3. Effects of Perceived Usefulness and Perceived Ease of Use on User Satisfaction

Perceived usefulness had a moderate positive effect on user satisfaction, thereby supporting H5. Students reported higher satisfaction when they perceived that the e-learning system improved access to knowledge, facilitated the distribution of learning materials, reduced the time required to complete academic activities, and increased learning efficiency. This finding is consistent with post-adoption theory, which positions satisfaction as an evaluative response formed when actual system use produces identifiable benefits. Ifinedo [92] found that perceived usefulness positively influenced satisfaction and continuance in technology-supported learning. Rajeh et al. [33] similarly identified perceived usefulness as a significant determinant of students' satisfaction and continuance intention toward e-learning.

Perceived ease of use had a statistically significant but substantively negligible effect on user satisfaction. H6 therefore received statistical support, but its practical relevance was limited. This pattern suggests that ease of use may function as a threshold condition. Once students become familiar with an institutional e-learning platform, further reductions in operational complexity may produce only marginal improvements in satisfaction. Research distinguishing pre-adoption and post-adoption stages has shown that effort-related expectations tend to decline in explanatory importance after direct experience, whereas perceived usefulness, expectation confirmation, and satisfaction become more influential [41].

Studies of e-learning continuance have similarly positioned perceived usefulness and satisfaction as more proximal determinants of sustained use [93]–[96]. Perceived ease of use may nevertheless remain relevant through indirect relationships with perceived usefulness, enjoyment, task–technology fit, or attitudes toward the platform [97]. Satisfaction may also be influenced by broader experiential factors, including social presence, instructional interaction, and expectation confirmation [98], [99]. Interface simplicity alone is therefore insufficient to produce a satisfactory e-learning experience.

The contrast between the moderate effect of perceived usefulness and the near-zero effect of perceived ease of use refines the application of TAM in a post-adoption setting. For experienced users, the principal evaluative question may no longer concern whether the platform is effortless to operate. Greater emphasis may instead be placed on whether the system produces meaningful academic benefits. This interpretation is consistent with the stronger effect of information quality, which directly influences students' ability to understand academic requirements, retrieve relevant content, and complete learning activities.

5.4. Effect of User Satisfaction on Continuance Intention

User satisfaction had a strong positive effect on continuance intention, thereby supporting H7. Satisfaction represents students' cumulative evaluation of the platform, the academic information it provides, and the extent to which prior system use has met learning expectations. When this evaluation is favorable, students are more likely to maintain the platform as part of their subsequent academic activities.

This finding is consistent with post-adoption research identifying satisfaction as a central predictor of sustained e-learning use. Satisfaction has been shown to increase students' online learning continuance intention [95], [100] and to strengthen continued engagement when prior expectations and perceived learning benefits are confirmed [52], [101]–[103]. Post-pandemic evidence also indicates that quality-based evaluations support continuance by generating favorable user experiences [104]. Research conducted in Indonesian higher education has similarly identified satisfaction as a major predictor of continued e-learning adoption [91], [105], [106]. The present findings extend this evidence by demonstrating a strong satisfaction–continuance relationship across five Indonesian universities.

The strong effect of satisfaction does not imply that institutional strategies should treat satisfaction as an isolated outcome. Satisfaction is formed through the interaction of technical performance, information quality, perceived usefulness, and prior user experience. In the present model, perceived usefulness was its most substantial direct antecedent, while perceived usefulness was strongly associated with information quality. This pattern suggests a possible sequence from quality to perceived value, evaluative response, and continuance intention.

The proposed sequence should not be interpreted as a confirmed mediation mechanism because indirect effects were not estimated. It nevertheless provides a theoretically coherent basis for future research. Longitudinal designs and bootstrapped mediation procedures are required to determine whether perceived usefulness and satisfaction transmit the effects of system quality and information quality to continuance intention.

6. IMPLICATIONS, LIMITATIONS & FUTURE RESEARCH

6.1. Theoretical and Practical Implications

The findings extend the integration of TAM and ISSM by indicating that information quality has greater explanatory relevance than system quality in post-adoption e-learning contexts. Students appear to evaluate institutional e-learning systems primarily as academic information environments, making the relevance, completeness, clarity, organization, and usefulness of learning content central to perceived usefulness and continuance intention. The weak effect of perceived ease of use on satisfaction further suggests that technical usability may function as a baseline requirement once users become familiar with compulsory institutional platforms, whereas perceived usefulness and satisfaction become more influential in explaining continued use.

These findings indicate that universities should integrate technical maintenance with systematic management of academic content. Institution-wide standards should regulate course-page structure, module sequencing, file naming, assignment instructions, deadline visibility, announcements, and feedback procedures. Evaluation instruments should distinguish technical usability from academic usefulness by assessing system reliability, accessibility, information accuracy, content relevance, organizational clarity, and alignment with learning requirements. This integrated approach may assist institutions in identifying whether limitations originate from technical performance, content management, instructional design, or academic communication.

6.2. Limitations and Future Research

The findings should be interpreted within several methodological limitations. The cross-sectional design does not permit temporal or causal inference, while purposive sampling restricts generalizability beyond students with comparable institutional and technological characteristics. The structural model was also respecified by correlating selected error terms, which may reflect sample-specific covariance. Future studies should therefore apply longitudinal designs, use probability-based or stratified sampling, and validate the revised model with independent samples across universities, academic disciplines, and levels of digital experience.

The study examined only direct relationships and measured continuance intention through self-reported responses. Subsequent research should test bootstrapped indirect effects involving perceived usefulness, perceived ease of use, and user satisfaction, while incorporating relevant contextual variables such as instructor quality, feedback responsiveness, interaction, self-efficacy, habit, voluntariness, digital stress, and task–technology fit [81], [84], [107]. Survey measures should also be combined with behavioral indicators, including login persistence, activity completion, submission punctuality, frequency of resource access, and duration of system use, to evaluate whether stated intentions correspond with sustained e-learning behavior.

7. CONCLUSION

This study provides evidence that TAM and ISSM can be integrated to examine students' continuance intention toward institutional e-learning systems in Indonesian higher education. The findings indicate that information quality is the strongest predictor of perceived usefulness, while satisfaction is the most immediate predictor of continuance intention. System quality remains statistically relevant but has weaker effects, and perceived ease of use contributes only minimally to satisfaction. These results suggest that sustained e-learning engagement depends primarily on the academic value, clarity, organization, and timeliness of learning information. Because the study used a cross-sectional, purposive, self-report design and a respecified SEM model, the findings should be interpreted as theory-consistent associations rather than causal evidence.

Universities should therefore prioritize the quality, clarity, organization, and timely updating of learning materials, instructions, feedback, and academic information while maintaining reliable system performance. Collaboration among lecturers, instructional designers, information-technology teams, and quality-assurance units is essential to strengthen students' perceived value, satisfaction, and continued use. However, the cross-sectional design, purposive sampling, model modification, and reliance on self-reported intention limit causal interpretation and generalizability. Future research should employ longitudinal designs, independent samples, mediation analysis, and actual usage data to validate and extend the proposed model across diverse higher education contexts.

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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 authors confirm that the study complied with all applicable local laws, ethical standards, and institutional guidelines, including obtaining approval from relevant ethics committees.

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