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A Sustainable Quality Model for Mobile Learning in Post-Pandemic Higher Education: A Structural Equation Modeling-Based Investigation

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Abstract: As an effect of the digital transformation encountered by higher education institutions in the post-pandemic phase, the current study aims to inspect the factors affecting the actual use of mobile learning among higher education students. A novel hybrid model based on the information system success and technology acceptance models was proposed and tested. The study included 400 undergraduate and postgraduate students from four Saudi universities who responded to a questionnaire consisting of two parts and seven dimensions, with a total of 26 items. For the analysis, a quantitative approach was applied using structural equation modeling. The results displayed that information quality had no impact on the actual use of mobile learning among higher education students. In contrast, other quality factors (system quality, service quality, and satisfaction) and perceived factors (perceived usefulness and perceived ease of use) had a positive effect. Accordingly, this study proposed an integrated framework to assist decision makers at higher education institutions in scaffolding students to develop their educational performance by depending on mobile applications comprising high-quality factors that address their real needs. This would also enable higher education institutions to enhance their digital transformation experience, thus contributing to achieving positive learning sustainability after the pandemic.

Keywords: actual using (AU); mobile learning (ML); information system success model (ISSM); technology acceptance model (TAM); structural equation modeling (SEM); higher education; Saudi Arabia

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1. Introduction

During the COVID-19 pandemic that swept the world in 2020, distance education became the ideal solution for educational institutions when all countries concurred on the complete closure of all their educational and non-educational institutions, resulting in the replacement of formal education with distance education [1,2]. This forced educational service providers to make formal and implicit modifications to their teaching and learning plans to comply with the imposed digital transformation, both adequately and rapidly [3,4].

Concurrently, the advancement in technology for mobile devices, apart from their low prices and the enormous potential functions that they can support [5], makes them more susceptible to periodic use [6]. In such a context, the multiple benefits and varied features of mobile learning (ML) have attracted several learners, especially in higher education [7]. ML is referring to a type of e-learning in which learning strategies can be implemented through smartphones or tablets [8]. ML has valuable features that support learners, including enabling free movement, easy availability, possibilities for self-study, facilitating interactions among learners or with teachers, and improved versatility and efficiency of information-sharing methods [9]. Furthermore, ML has become an important complementary tool for digital learning strategies in both K-12 and higher education because of its positive impact on all participants in these systems—it positively affects the attitudes of participants and works to enhance their perceptions toward this kind of learning [10]. It is worth noting that this role became more evident after the COVID-19 pandemic, during which mobile learning became a distinguishing feature of the time [11,12]. Moreover, the wide usage of mobile devices and the consequent adoption of ML in many learning systems [13] have enabled it to play a positive role in a learner-centered learning environment by negating the constraints of time and space [14]. Moreover, several studies have indicated the multiple factors and advantages of ML for learners, such as its affordable cost, focus on the completion of educational tasks, and controls on the availability of information, in addition to being an educational tool with a remarkable ability to link the formal learning contained in lectures with informal knowledge gained through external learning [15,16]. Thus, the concept of ML has led to the expansion of the scope of educational opportunities in higher education, providing learners with new learning opportunities that allow them to be aware of the context of the learning as well as encourage sharing and cooperation [17]. ML has also made it possible to access educational content globally in a way that further enhances interactions between individuals who find one-on-one communication difficult, thus leading to more effective learning [16]. In addition, it enables the highly efficient reuse of learning materials, along with the availability of individually reinforced learning systems, which enhances the sustainability of learning [18].

Furthermore, the almost complete digital transformation, especially during the COVID-19 pandemic, that was imposed on all educational institutions at the higher education level indicates the need to rely on e-learning management systems, as well as ML applications [19]. In particular, the auditors of studies on the criteria for developing ML applications found that these studies are still in their initial stages—they have not extensively explored all relevant quality factors at the level of both design and content [20,21]. These factors can enhance the experience of the actual use of ML applications by integrating them with other e-learning environments, such as e-learning management systems, or by using them separately [14].

Drawing on this same context, it is probable that the experience of sustainable learning can be enhanced through learning environments based on ML, as it is designed based on the philosophy of abundance and therefore includes a variety of learning resources [22]. Moreover, this can contribute to achieving the fourth goal for sustainable development, as established by the United Nations, concerning ensuring the quality of education [23]. Accordingly, the current study seeks to examine the factors affecting the actual use of ML among higher education students in the post-pandemic phase to analyze the sustainability of this type of learning and identify whether it enhances the effective learning experience of students. Accordingly, the current study's purpose is to answer the following primary question:

What are the most relevant quality factors derived from the information systems success (ISSM) and technology acceptance models (TAM) in terms of achieving satisfaction and the actual use of ML to support and sustain higher education students' learning in the post-pandemic phase?

2. Literature Review and Development of Hypotheses and the Research Model

This section is divided into two parts—the first explores the theoretical framework and research related to the variables considered in the current study, while the second presents the current hypotheses.

2.1. Literature Review

This section establishes the theoretical framework and examines previous research related to the variables considered in the current study—ML, ISSM, and TAM—as presented below.

2.1.1. Mobile Learning (ML)

ML concerns integration between different types of handheld devices and wireless networks to support teaching and learning processes by providing and presenting educational practices in a digital form, thus enabling students to access learning content anywhere and at any time [20]. In the current study, ML refers to innovative technology that utilizes mobile devices to scaffold higher education students at the level of providing content, practicing educational activities, or conducting evaluations.

The use of ML in higher education has become a high priority due to the valuable rewards it provides—enabling students to access learning anytime and anywhere, playing an active role in helping teachers depend on diverse learning strategies to counter individual differences, and allowing learners to efficiently perform their educational tasks [22]. In higher education, ML supports learning activities for approximately 67% of learners [21]. Moreover, in the Kingdom of Saudi Arabia, the field of higher education has been making concerted efforts to integrate ML applications into teaching and learning settings, with the aim of encouraging students and enabling them to adopt these applications as basic tools for learning [24]. In 2016, Saudi Arabia's Crown Prince announced an aspirational federal plan, Vision 2030, which focused greatly on education [25]. As a result, many initiatives were launched to promote and activate the use of ML in the education sector at the university level, in addition to strengthening the technical infrastructure within the corridors of these universities at the hardware and software levels. Furthermore, in early 2022, King Faisal University launched the first educational application, Kofu to support student learning both inside and outside classrooms. Apart from this, efforts have been made to achieve comprehensive educational management at the level of both faculty and staff members [11].

Despite these practices, ML in the Kingdom of Saudi Arabia is still in its introductory stage in terms of management and implementation [26]. This method is still relatively new and faces certain limitations in its use, with students' acceptance being one of the most crucial limitations [4]. Therefore, the current study seeks to examine the factors that influence the success of ML as an information system and its acceptance by higher education students.

2.1.2. Information System Success Model (ISSM)

The success of the information system has drawn the attention of many scholars and e-learning program developers, especially in the higher education sector. Scholars have made tremendous efforts to determine the most crucial factors responsible for the success of an information system. The information system success model (ISSM), which was developed by Dillon and Mclean [27], proposes six factors to determine the quality of innovations. Many studies have proved that these factors of quality, such as information quality, system quality, and service quality, comprise characteristics that lead to a positive experience for the learner, which contributes to increasing the number of end users for the model. Several studies have also suggested that satisfaction promotes more intention to use in the future [28,29]. These results can, in turn, be considered the basis for future studies. Accordingly, the current study restricted its analyses to examining information quality, system quality, service quality, and satisfaction.

2.1.3. Technology Acceptance Model (TAM)

Educational and technical fields have proposed various theories for determining learners' acceptance of information technology systems. Among them, the technology acceptance model (TAM), developed by Davis [30], is the largest extensive model utilized in studies associated with the acceptance of communication and information systems. The theory of reasoned action (TRA) is considered the basis for deriving TAM factors, where the model is interested in describing and studying the efficacy of external variables on the internal thoughts of individuals. Furthermore, this theory suggests interrelated logical relationships among perspectives, beliefs, and behavioral intentions that successively predict the actual use of information systems and communications [30]. The TAM model comprises two main factors that govern the internal beliefs of individuals—perceived usefulness and perceived ease of use. The first highlights the extent to which a person believes that utilizing a specific system will improve production, while the second states the rate at which a person postulates that using the system will be easy or involve minimal effort [31].

Notably, many relevant studies have indicated that both of these factors are well suited for the recognition of learners' perceptions of using ML [32,33]. These studies identified TAM as an efficient model for estimating the factors contributing to learners' acceptance of ML in different learning contexts and at the level of both intention to use and actual use. However, they did not consider the external factors that have a negative impact, thus limiting the explicative abilities of the model, which, in turn, leads to a decrease in its ability to estimate the factors of acceptance of the proposed system. Accordingly, there is a critical need to add further relevant external factors that are under tight control. As a result, the current study integrated the TAM with the ISSM, since the former does not account for quality factors, while the latter does not regard the intention or actual use factors.

2.2. Development of Hypotheses and the Research Model

Many relevant studies in the domain of educational technologies have examined students' acceptance of ML factors considering their behavioral intentions based on some behavioral theories, such as the unified theory for acceptance and use of technology (UTAUT) [34]. Although many studies have relied on the ISSM independently to investigate the success of an information and communication system based on factors of quality and its effect on net benefits and intention to use [29,35–37], these previous empirical studies did not examine the function of quality factors in the ISSM in measuring students' actual use expectations for ML, especially in the post-pandemic phase, to sustain digital learning. Accordingly, this study was conducted to identify whether, in addition to technological acceptance factors, quality factors also affected the satisfaction of higher education students with the actual use of ML in the post-pandemic period. The current study suggests a hybrid model that combines ISSM and TAM to evaluate quality factors, perceived usefulness, and perceived ease of use as major drivers of student satisfaction, which can influence students' actual use of ML.

Likewise, quality education can also help developing societies improve their economic conditions, especially when delivered through learning systems based on ML [38]. The COVID-19 pandemic has certainly created a new routine for human life, especially in the education sector, where new digital teaching and learning environments embody the digital transformation phase. These environments are based on what is known as green skills [39]—skills that depend on reducing waste, in terms of both natural and human resources—that can help achieve sustainability in education [39]. The current study considers the possibility of realizing this concept by relying on ML, since this technology has several functional capabilities in terms of design, presentation, interaction, and sharing, entailed in its characteristics [40]. This is especially true when it is designed based on quality factors based on the ISSM and perceived intentions based on the TAM.

In the sections below, the hypotheses presented in the current study are displayed. The ISSM has been considered to estimate the quality factors affecting actual use, relying on information quality, system quality, service quality, and satisfaction. Meanwhile, TAM was estimated with reference to students' preferences regarding perceived usefulness, perceived ease of use, and actual use.

2.2.1. Information Quality (IQ)

Information quality is considered the fundamental feature of the adoption of an e-learning system at the higher education level [41]. Along with the satisfaction factor, information quality has a great effect on learners' intentions to use a proposed system, regarding both perceived usefulness and perceived ease of use [42,43]. Despite this, only a few relevant studies have investigated the role of the information quality factor on the satisfaction and the actual use of ML among higher education students, especially in the post-pandemic phase. Considerable frameworks have been suggested to measure information quality—applicability, domain, precision, promptness, wholeness, and information effectiveness [27]. Accordingly, the current study selected learning content quality and content design quality as factors integral to achieving good information quality. Learning content quality discusses to the appropriateness of the learning context for students in terms of its relevance, completeness, and accuracy [41], while content design quality refers to the styles and presentation techniques used in the learning content modules [32]. In addition to providing educational content in multiple forms (texts, graphics, sounds, videos, animations, etc.), ML is easily accessible due to its usage of a variety of learning strategies, such as lectures, assignments, tests, etc. [4]. Based on this context, the current study sought to critique the actual use of ML among higher education students when factors such as good content design are associated with students' educational needs and preferences. Accordingly, the current study suggests the hypothesis below:

Hypothesis 1 (H1): *The information quality through ML will positively affect satisfaction among higher education students.*

2.2.2. Actual Use (AU)

The actual use (AU) is an indicator for estimating the realistic behavior of e-learning systems [30]. Many scholars have confirmed that the AU factor is highly correlated with the adoption of a novel system [4,44,45]. Furthermore, as that which represents the major construct of TAM, the current study employed AU to predict the use of ML among higher education students. Effectively, the following hypothesis is suggested:

Hypothesis 2 (H2): *The information quality through ML will positively affect AU among higher education students.*

2.2.3. System Quality (SQ)

System quality indicates the quality of the action and functionality of the information and communication system in terms of instructional design, procedures, and resources used to achieve general quality in the system. Moreover, it describes the valuable capabilities provided by the information and communication system [27]. Several studies have indicated that the quality of a system is a pertinent criterion factor in evaluating the attainment of its goals [32,46] and is a key factor in students' satisfaction and intention to use, which ultimately leads to enhanced usage of the system [47]. Since system quality depends on the perceptions of the users, properly designing a system with high levels of quality factors, such as accessibility to educational items, as well as high levels of utility, leads to positive awareness for students that the system will be easy to use [29]. However, studies assessing the effects of system quality on user satisfaction and AU are rare, especially those related to the use of ML among higher education students in the post-pandemic phase. Overall, system quality can be estimated through a set of dimensions, including shareability, friendly user interface design, ease of use, integration of functions, interactivity, flexibility, and background of the study [27]. The current study addressed the system quality factor of ML based on the following set of dimensions—being an easy means of communication, the possibility of integration with related applications, accessibility, easy downloading and uploading, and an effective user interface. Based on this discussion, the current study suggests two hypotheses, as presented below:

Hypothesis 3 (H3): *The system quality through ML will positively affect satisfaction among higher education students.*

Hypothesis 4 (H4): *The system quality through ML will positively affect AU among higher education students.*

2.2.4. Service Quality (SEQ)

In the case of information and communication systems, service quality highlights the entire excellency of services that the student can predict [48]. Service quality can be specified as the characteristic features of the services that end users acquire from the information and communication system [27]. It is considered a pivotal factor in the responsible efficacy of an e-system [46]. Furthermore, studies have shown that students' satisfaction and intention to use are highly assumed by service quality, which eventually shows enhanced student use of the proposed e-system [47,49,50]. Service quality is estimated by an expansive set of dimensions—quality guarantee, prompt response, empathy, availability, and customization. Notably, the background of the concerned study should be considered when selecting service quality factors [27]. The current study estimated the service quality factor based on the following dimensions—availability, quality guarantee, and rapid response. Accordingly, the hypotheses below were addressed:

Hypothesis 5 (H5): *The service quality through ML will positively affect satisfaction among higher education students.*

Hypothesis 6 (H6): *The service quality through ML will positively affect AU among higher education students.*

2.2.5. Perceived Usefulness (PU)

The conception of perceived usefulness is detailed as the range to which an end user perceives that utilizing the e-system will develop his/her educational outcomes [32]. Students with a higher system utility perception are certainly more likely to use information systems more efficiently [4]. Perceived usefulness is also a vital factor in positively influencing the intention to use and, therefore, AU [51]. Furthermore, previous studies have found a positive and significant effect of perceived usefulness on intensifying the intention to use an e-learning system [4]. Accordingly, the current study addressed the hypothesis below:

Hypothesis 7 (H7): *The perceived usefulness through ML will positively affect AU among higher education students.*

2.2.6. Perceived Ease of Use (PEU)

Perceived ease of use indicates the extent to which a specific perceives that using the e-system will be effortless [32]. Studies have indicated that individuals' impressions of the acceptance of ML applications or AU are significantly emphasized by the perceived ease of use [48,52]. The related literature has also indicated that the intention to use ML and their AU are positively swayed by perceived ease of use [53]. Accordingly, the current study addressed the hypothesis below:

Hypothesis 8 (H8): *The perceived ease of use through ML will positively affect AU among higher education students.*

2.2.7. Satisfaction (S)

Satisfaction is defined as the range to which a system fully achieves the requirements and demands of its clients [32]. It also indicates the degree of users' satisfaction with the services entailed in the proposed system [54]. Several relevant studies have confirmed that satisfaction is a critical and influential factor that greatly influences the intention to use, along with AU [27,41]. Accordingly, the hypothesis below is suggested:

Hypothesis 9 (H9): *The satisfaction through ML will positively affect AU among higher education students.*

Based on these findings, the current study aimed to address the factors affecting the AU of ML among higher education students in the post-pandemic phase. Six factors were identified, based on both the ISSM and the TAM. While information quality, system quality, service quality, and satisfaction are the factors regard with the ISSM, perceived usefulness and perceived ease of use are those related to the TAM, as shown in Figure 1.

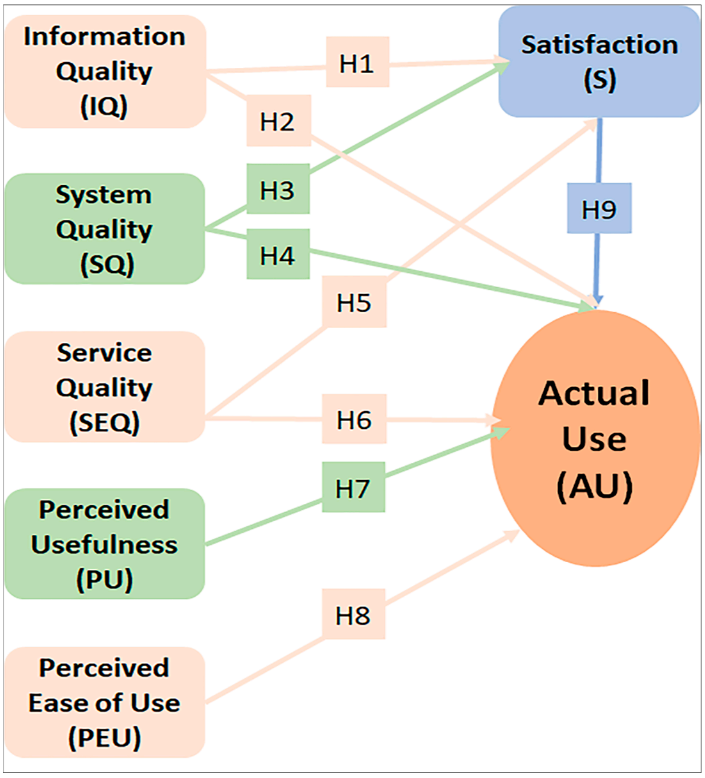

Figure 1. Proposed theoretical model and hypothesis.

3. Materials and Methods

This section has been divided into three sections to provide adequate descriptions of the study procedures involved in this research.

3.1. Study Sample

A total of 400 students, both male and female, from four Saudi universities in their second semester participated in the current study, some of whom were enrolled as undergraduates, while others were postgraduates for the academic year 2021–2023. Ethical approval to accomplish the current study was gained from the Scientific Research Ethics Committee at King Faisal University, registered as KFU- REC - 2021- DEC - EA000320. The demographic data of the study sample are presented in Table 1. The normal distribution for the participants was calculated as a condition for developing the next statistical procedures. Moreover, the normal distribution for the sample in terms of age was (Mean = 2.15, Standard Deviation = 0.674, N = 400), and the normal distribution for the sample in terms of gender was (Mean = 1.56, Standard Deviation = 0.497, N = 400). The students were also given the opportunity to provide their agreement to involve in the study, with the freedom to leave whenever they requested.

Table 1. The study sample demographic data through descriptive statistics.

Item		Number and Percentage	Mean	Standard Deviation
Gender	Male	175 (43.8%)	1.56	0.49
	Female	225 (56.2%)		
Age	≤20	39 (9.8%)	2.15	0.67
	21:25	288 (72%)		
	26:30	47 (11.8%)		
	>30	26 (6.4%)		
Faculty	Education	259 (64.7%)	1.94	1.55
	Arts	33 (8.2%)		
	Agriculture Sciences	32 (8.2%)		
	Finance	43 (10.7%)		
	Other	33 (8.2%)		
Academic Major	Scientific	147 (36.8%)	1.63	0.48
	Literary	253 (63.2%)		
Stage	Undergraduate	71.0 (71.0%)	1.29	0.45

3.2. Study Instrument

To measure the factors impacting the AU of ML applications among higher education students, a questionnaire was developed established on the foregoing theoretical framework, especially those related to the ISSM and the TAM, from which the questionnaire dimensions and items were Derived [4,27,32,49]. The total number of points in the questionnaire was 26, which were distributed over the following seven aspects—the information quality aspect (four points), the system quality aspect (four points), the service quality aspect (four points), the perceived usefulness aspect (four points), the perceived ease of use aspect (three points), the satisfaction aspect (four points), and the AU dimension (three points). To calculate the interrater and content validity, the questionnaire was presented to three experts in the instructional technology field. The experts indicated that the questionnaire was highly suitable and relevant to the objectives and levels and that the items were precise, scientifically accurate, and relevant to the constructs and to the procedure that the students would undergo. A five-point Likert scale was adopted to estimate the students' scores on the questionnaire (strongly disagree = 1; disagree = 2; neutral = 3; agree = 4; strongly agree = 5). The scores for the questionnaire ranged from 26 (lowest) to 130 (highest). See Appendix A for more details.

3.3. Pilot Study

When conducting the pilot study, 100 male and female students—not those in the main study sample—calculated the questionnaire's statistical validity and reliability. The SPSS program (v. 26) was used for this purpose. The questionnaire's Cronbach's alpha values were estimated to measure the factors affecting the AU of ML among higher education students, as presented in Table 2. The total alpha coefficient assessment of the questionnaire was 0.917, which indicates an eminent reliability coefficient. The first column from the right exhibitions the alpha coefficient of Cronbach (with the number of questionnaire items), where the alpha coefficient extended from 0.906 to 0.917. Accordingly, all the items were found to be stable and contributed to raising the overall questionnaire's reliability. The second column presents the entire score of the questionnaire's correlation coefficient when removing one of the item's scores. This coefficient indicates the questionnaire's item validity, as the correlation coefficients ranged from 0.286 to 0.697. The consequences illustrate that they are significant at the 0.01 level, which indicates that all the questionnaire items had statistical validity.

Table 2. The questionnaire's reliability and validity coefficients (n = 100).

Item	Cronbach's Alpha Coefficient if the Item Is Omitted	The Coefficient of Correlation of the Item with the Entire Score of the Questionnaire
Information Quality (IQ1)	0.910	0.409
Information Quality (IQ2)	0.908	0.530
Information Quality (IQ3)	0.911	0.419
Information Quality (IQ4)	0.909	0.547
System Quality (SQ1)	0.909	0.512
System Quality (SQ2)	0.907	0.669
System Quality (SQ3)	0.909	0.514
System Quality (SQ4)	0.910	0.431
Service Quality (SEQ1)	0.912	0.352
Service Quality (SEQ2)	0.907	0.674
Service Quality (SEQ3)	0.910	0.466
Service Quality (SEQ4)	0.909	0.484
Perceived Usefulness (PU1)	0.917	0.387
Perceived Usefulness (PU2)	0.911	0.386
Perceived Usefulness (PU3)	0.909	0.503
Perceived Usefulness (PU4)	0.911	0.374
Perceived Ease of Use (PEU1)	0.908	0.537
Perceived Ease of Use (PEU2)	0.913	0.286
Perceived Ease of Use (PEU3)	0.910	0.465
Satisfaction (S1)	0.908	0.550
Satisfaction (S2)	0.907	0.619
Satisfaction (S3)	0.906	0.637
Satisfaction (S4)	0.906	0.679
Actual Use (AU1)	0.906	0.686
Actual Use (AU2)	0.909	0.523
Actual Use (AU3)	0.906	0.697

4. Statistical Data Processing and Results

This section offers the data analysis process of the measurement model, as well as the statistical results of the structural model proposed in this study, grounded on the ISSM and TAM.

4.1. Data Analysis of the Measurement Model

Figure 2 notes the items and latent factors of students' AU of ML through ISSM and TAM using the measurement model. In the next level, structural equation modeling (SEM) and third-order confirmatory factor analysis (CFA) were adopted to analyze the measurement model. The Amos program (v. 25) was used for this purpose. There are some tools that can be adopted as indices to assess the model estimation. According to Hu and Bentler [55], Byrne [56], and Kline [57], the normed chi-square, chi-square/degree of freedom, root-mean-square residual (RMR), goodness-of-fit index (GFI), adjusted GFI (AGFI), normed fit index (NFI), relative fit index (RFI), incremental fit index (IFI), Tucker–Lewis coefficient (TLI), comparative fit index (CFI), and the root-mean-square error of approximation (RMSEA) are the tools that can be used to estimate the model as offered in Table 3. The outcomes indicate the manifestation of positive fitness indicators in the measurement model. Moreover, both the composite reliability (CR), average variance extracted (AVE), square roots of AVE (discriminant validity—DV), and Cronbach's Alpha were calculated. Table 4 displays the values for the CR, which ranged between 0.807 and 0.929. Alongside, AVE ranged from 0.591 to 0.667. Moreover, the DV ranged between 0.751 and 0.965. All values matched the recommendations stated by Fornell and Larcker [58].

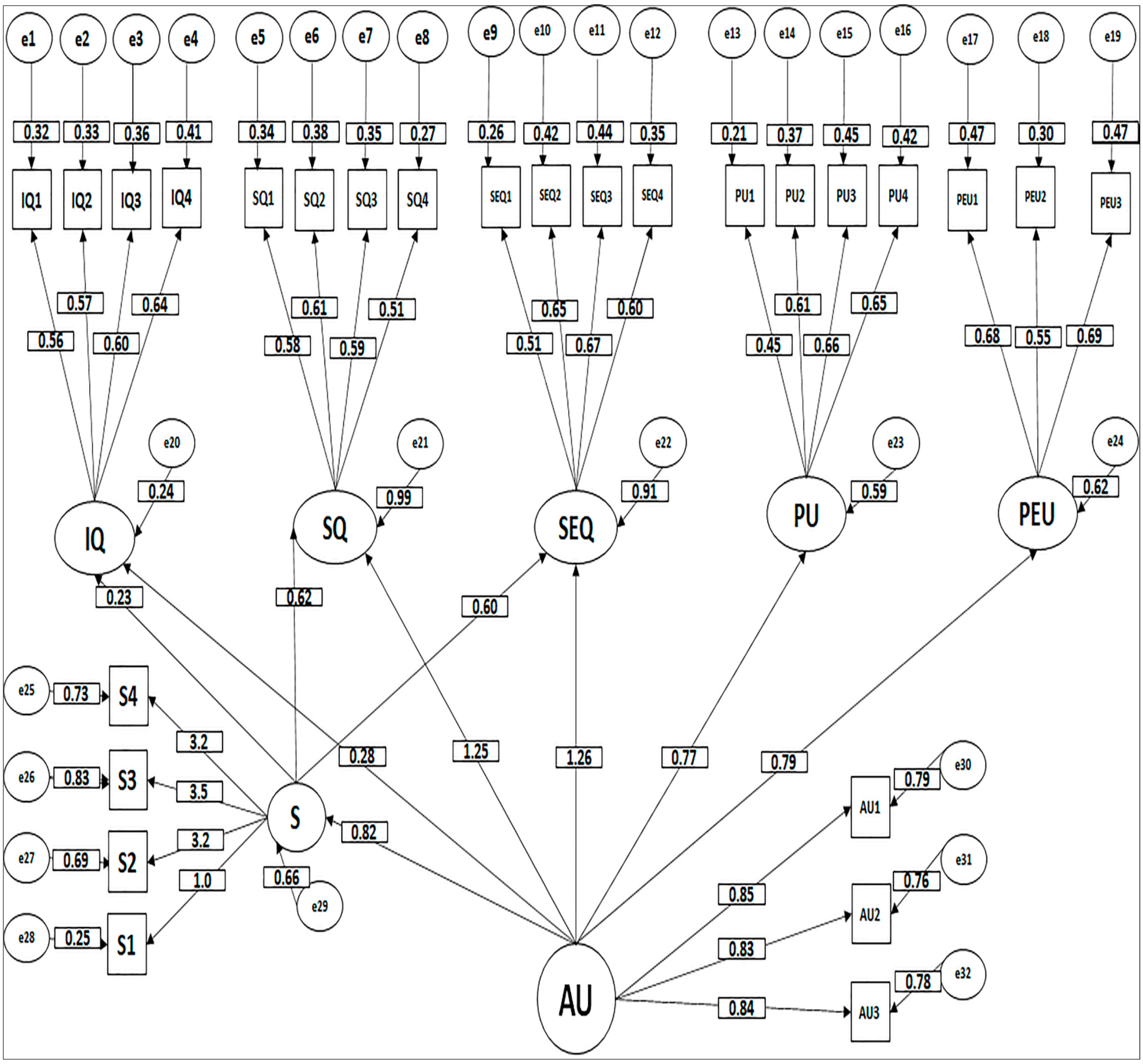

Figure 2. The measurement model for actual use of ML.

Table 3. The quality indicators for the measurement model (n = 400).

Measure Type	Supported Values	Measurement Model's Values
508.688/204 = 2.494	≤3.5–0 (perfect fit) and (ρ > 0.01)	Chi-square (χ2)
2.494	Value should be >1.0 and <5.0	Normed chi-square (χ2)
0.043	Goodness should be <0.05	(RMR)
0.901	Goodness should be ≥0.90	GFI
0.926	Goodness should be ≥0.90	AGFI
0.919	Goodness should be ≥0.90	Normed fit index (NFI)
0.938	Goodness should be ≥0.90	Relative fit index (RFI)
0.917	Goodness should be ≥0.90	Incremental fit index (IFI)
0.906	Goodness should be ≥0.90	Tucker–Lewis index (TLI)
0.916	Goodness should be ≥0.90	Comparative fit index (CFI)
0.06	<0.10 indicates a good fit, and <0.05 is considered a very good fit	Root-mean-square error of approximation (RMSEA)

Table 4. Calculating composite reliability, convergent validity, and discriminant validity for the measurement model (ISSM and TAM).

Latent Variables	CR > 0.7	AVE ≥ 0.5 < CR	(DV) > Correlation	Cronbach's Alpha
Information Quality	0.807	0.601	0.751	0.758
System Quality	0.912	0.642	0.862	0.852
Service Quality	0.851	0.614	0.855	0.848
Perceived Usefulness	0.928	0.639	0.869	0.878
Perceived Ease of Use	0.864	0.621	0.845	0.892
Satisfaction	0.907	0.667	0.923	0.846
Actual Use	0.929	0.654	0.965	0.857

4.2. Data Analysis of the Proposed Structural Model

Using the CFA method, SEM was implemented in the existing study to examine the factors guiding the AU of ML among higher education students through ISSM and TAM. Figure 3 shows the path analysis method for accepting seven hypotheses while rejecting two others. The main statistics and assumptions of the structural model suggested in this study are revealed in Table 5. An examination of the unstandardized coefficient (β) and standard error (SE) estimates suggests that the basic statistical indicators found the model to be a good fit.

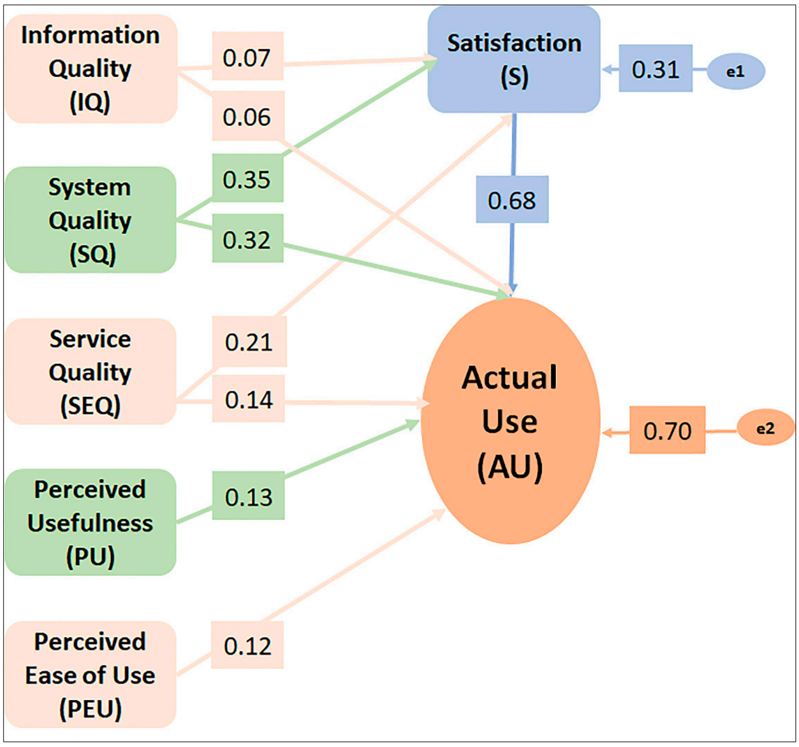

Figure 3. Proposed model's results for actual use of ML.

Table 5. Testing the structural model hypotheses.

Hypotheses	Path	Estimate	S.E.	*t*-Value	*p*	Results
H1	IQ → S	0.071	0.073	1.374	0.169	Unsupported
H2	IQ → AU	0.060	0.044	1.597	0.110	Unsupported
H3	SQ → S	0.349	0.083	5.876	0.000	Supported
H4	SQ → AU	0.320	0.052	5.491	0.000	Supported
H5	SEQ → S	0.208	0.078	3.596	0.000	Supported
H6	SEQ → AU	0.164	0.049	3.333	0.000	Supported

Table 5. *Cont.*

Hypotheses	Path	Estimate	S.E.	*t*-Value	*p*	Results
H7	PU → AU	0.133	0.045	2.314	0.000	Supported
H8	PEU → AU	0.123	0.029	1.231	0.000	Supported
H9	S → AU	0.683	0.029	20.759	0.000	Supported

4.3. Statistical Results of ISSM and TAM

According to the structural model and its attributes offered in Table 5, in the case of the AU of ML, the information quality factor has no effect on satisfaction among higher education students, as reflected by the actuality of a negative association between information quality and satisfaction (t = 1.374, β = 0.071, $p < 0.001$). As a result, the first hypothesis was rejected. Likewise, there is no impact was identified concerning the information quality factor and the AU of ML among higher education students (β = 0.060, t = 1.597, $p < 0.001$), which rejected the second hypothesis. Additionally, the consequences exposed that the system quality factor positively affects the satisfaction factor in terms of the AU of ML among higher education students (β = 0.349, t = 5.876, $p < 0.001$). This result effectively indicated that the third hypothesis is acceptable. Furthermore, the system quality factor was found to affect the AU factor positively (β = 0.320, t = 5.491, $p < 0.001$). Accordingly, the fourth hypothesis was approved. The results also displayed that the service quality factor positively affected the satisfaction factor in the AU of ML among higher education students, where β = 0.208, t = 3.596, and $p < 0.001$. The fifth hypothesis, therefore, was consented to. Similarly, the service quality factor was identified as having a positive effect on the AU factor (β = 0.164, t = 3.333, $p < 0.001$), confirming the sixth hypothesis. In addition, Figure 3 and Table 5 illustrate that perceived usefulness has an affirmative outcome on the AU of ML among higher education students (β = 0.133, t = 2.314, $p < 0.001$)—a finding that supported the seventh hypothesis. Similarly, perceived ease of use was detected to positively impact AU (β = 0.123, t = 1.231, $p < 0.001$), thus confirming the eighth hypothesis. Finally, the results also showed that satisfaction has a positive effect on the AU factor of ML among higher education students (β = 0.683, t = 20.759, $p < 0.001$). Accordingly, the ninth hypothesis was proved.

5. Discussion and Implications

The current study sought to examine the quality factors that influence the satisfaction of higher education learners and their AU of ML through the proposed theoretical model based on ISSM and TAM to better understand students' behaviors that affect their use of these applications, especially in the post-pandemic phase, to achieve learning sustainability.

This study differs from the previous literature in many aspects. Some earlier studies examined only the quality factors and precisely investigated the factor of intention to use. In contrast, the current study is concerned with investigating the effects of these quality factors on the AU of ML based on the satisfaction factor. In addition, this study is one of the few to inspect quality factors in the field of ML applications based on a proposed theoretical model whose application to the Saudi Arabian context is novel, since this territory is rarely subjected to such a treatment involving the integration of theoretical models to provide justification for the functions acted by quality factors, besides individual beliefs in the AU of ML applications. Accordingly, this study supports critical suggestions and presumptions for university administrators, systems, and application designers by estimating the perceptions of the AU of ML applications among higher education students and inspecting their behavior patterns in a way that achieves sustainable learning, especially in the post-COVID-19 phase.

The study results got that the information quality factor has no influence brunt on both satisfaction and AU, which contradicts studies [28,46,59] whose results indicate that providing educational content that meets the factors of completeness, integration, and quality, along with diversity in terms of presentations, tasks, reports, assignments, etc., leads to the creation of more efficient educational content for ubiquitous learning, which ultimately helps achieve satisfaction and wider AU of the system. Alternatively, consistent with the consequences of the current study, Seta et al. [60] showed that the information quality factor does not affect both the satisfaction and the intention to use e-learning systems among higher education students. The current study findings may have been derived as a result of reliance on the selected dimensions of information quality, which were confined to the quality of the learning content and the content design. This highlights the urgent need to periodically poll students about their points of view on the most appropriate dimensions of information quality.

The study results also identified that the system quality factor has a weighty influence on satisfaction and AU. This is consistent with the studies conducted by Novianto [61] and Seta et al. [60], which detected a major impact of system quality on satisfaction and intention to use. These results demonstrate that the system quality factor has some crucial indicators that should be considered in systems based on ML. Moreover, student interactions in application-based ML allow more effective and equal interactions not only among themselves but also with their teachers. Furthermore, these applications enable them to exchange and share learning content efficiently [28,62]. Apart from this, system quality includes the possibility of the e-learning system enjoying various communication tools, such as discussion rooms, instant messages, live and recorded lectures, etc. This may enrich students' learning experiences, thus contributing to increased AU of these systems in the future [62,63]. Furthermore, a well-designed user interface that contains menus, bars, and control tools can reduce the effort involved in using educational applications, which would help students realize that they are easy to use [64,65]. In addition, if mobile learning applications provide students with online access to download educational materials anytime and anywhere, it will help them consider these applications useful tools for learning, thus ensuring sufficient AU over time [66].

In addition, the consequences of the current study showed that service quality has a positive influence on both satisfaction and AU. The results of Alksasbeh et al. [29] and Almaiah and Al-Khasawneh [66], which identified a significant impact of service quality on satisfaction along with the intention to use ML, are consistent with this finding. However, the current result contradicts those of Seta et al. [60] and Uppal et al. [67], who stated that the service quality factor does not affect the e-learning system regarding satisfaction and AU among higher education students. This result is derived from the fact that designing an educational application based on ML involves high service quality factors, such as integrated online support with availability features, that can increase access to learning content in a more flexible and efficient manner. This, in turn, would enhance the application of the concept of massive open online courses (MOOCs) and take advantage of its various features by relying on mobile devices instead of desktops. In addition, indicators of other service quality factors considered in this study, such as availability, quality of guarantee, and rapid response, could work to support learning strategies, such as collaboration, to engage students in e effective learning procedures.

The results of the current study also revealed that both perceived usefulness and perceived ease of use have major impacts on the AU of ML among higher education students. Notably, the finding indicating the superiority of perceived usefulness over ease of use is consistent with the findings of Al-Adwan [68], Bazelais et al. [69], Hu et al. [70], and Venkataraman and Ramasamy [71]. This confirms the significant use of ML applications in learning by the students involved in the recent study. This is also an indicator for attracting the interest of those in charge of e-learning systems in higher education institutions, especially in the case of those relevant to ML and to the need to improve the usefulness of these systems while investing in ease of use. In addition, this improvement may lead to the development of students' actual usage perceptions. Moreover, the current results showed that student satisfaction has a significant positive influence on the AU of ML, which is consistent with those of the studies managed by Aldholay et al. [72], Alksasbeh et al. [29], Aldholay et al. [73], Alzahrani et al. [49], Aldholay et al. [74], and Al-Abdullatif et al. [75].

6. Conclusions, Implications, and Limitations

The current study proposes an in-depth framework to assess the influence of quality factors on behavioral patterns among higher education students in relation to ML sustainability. This framework was constructed based on a merged hybrid model involving ISSM and TAM, focusing particularly on the post-pandemic stage. The study results identified that both system quality and service quality factors significantly influenced students' satisfaction and AU of ML in higher education. However, the information quality factor showed no effect on students' satisfaction or AU. The results also revealed that perceived usefulness and perceived ease of use positively influenced students' AU, but the satisfaction factor was the major contributor to the AU of ML among higher education students.

Consequently, the current study has several implications for the theoretical and practical viewpoints related to this topic. From a practical viewpoint, these results can guide educational application developers in building ML applications more effectively and efficiently. Meanwhile, from a theoretical viewpoint, understanding students' actual needs can lead to the development of better systems for related applications. Furthermore, decision makers at higher education institutions can facilitate and develop student participation by using ML technology to promote the perceived behaviors that control AU. Moreover, positive attitudes among students toward adopting this technology need to be fostered through actions such as providing diverse opportunities for learning, granting appropriate learning content, and ensuring the high quality of the learning procedures and the resulting outcomes.

The current study also has several limitations. First, this study was conducted in four Saudi public universities involving 400 undergraduate and postgraduate students. In this context, future studies should not only account for private universities, but also expand the study sample to include a larger number of Saudi and non-Saudi students with different educational, psychological, and demographic characteristics, which would lead to a comprehensive generalization of the research results. Second, the current study relied on a few selected factors of quality and technology acceptance to measure the AU of students. Future studies must adopt other theoretical models that can accurately measure the attitudes of higher education students toward the use of ML, for example, the task technology fit model (TTFM) and the unified theory for acceptance and use technology (UTAUT). Third, while the current study adopted a descriptive approach, future research may adopt experimental approaches to measure the effectiveness of ML applications established regarding the factors of quality and technology acceptance on different learning outcomes.

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Data Availability Statement: Data are unavailable due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. The Survey Questionnaire for the AU of ML among Higher Education Students

The First Section: Demographical Characteristics
Gender: A. Male: B. Female:
Age A. Less than 20 years old B. 20–25 C. 26–30 D. More than 30 years old
Faculty: . . . . **Academic major:** . . . . **Stage:** . . . .
The second section: The 5-point Likert Scale Strongly disagree = 1 Disagree = 2 Neutral = 3 Agree = 4 Strongly agree = 5

5	4	3	2	1	Reference	Statement	Construct
						Information Quality At the ML.	
					DeLone and McLean (2004) [27] and Almaiah and Alismaiel (2019) [32]	Mobile learning applications provide what is related to my educational needs.	Information quality 1
						Mobile learning applications provide extensive and accurate information.	Information quality 2
						Mobile learning applications provide what I really need in an updated way.	Information quality 3
						Mobile learning applications provide information and content in an organized way.	Information quality 4
						System Quality At the ML.	
					DeLone and McLean (2004) [27]	Mobile learning applications provide an easy way to communicate with my teachers.	System quality 1
						Mobile learning applications provide the possibility of merging and linking with other related educational applications.	System quality 2
						Mobile learning applications provide the ability to download and upload files easily.	System quality 3
						From my point of view, acceptable mobile learning applications are characterized by: dimensions, display resolution, menus, and icons of high design quality.	System quality 4
						Service Quality At the ML.	
					DeLone and McLean (2004) [27] and Alzahrani et al. (2019) [49]	Mobile learning applications provide educational services anywhere.	Service quality 1
						Mobile learning applications provide educational services at any time.	Service quality 2

						Mobile learning applications provide an excellent service.	Service quality 3
						Mobile learning applications allow teachers to respond collaboratively well.	Service quality 4
Perceived Usefulness At the ML.							
					Davis (1989) [30] and Venkatesh (2003) [31]	Mobile learning applications help me finish my educational tasks efficiently and quickly.	Perceived Usefulness 1
						Mobile learning applications enable me to improve learning outcomes.	Perceived Usefulness 2
						Mobile learning applications develop my scientific productivity.	Perceived Usefulness 3
						Mobile learning applications are effective and efficient.	Perceived Usefulness 4
Perceived Ease of Use At the ML.							
					Davis (1989) [30] and Venkatesh (2003) [31]	I find mobile learning applications familiar to use.	Perceived ease of use 1
						I find mobile learning applications, they do not need more mental effort.	perceived ease of use 2
						In general, mobile learning applications are easy to use.	perceived ease of use 3
Satisfaction At the ML.							
					DeLone and McLean (2004) [27]	Mobile learning applications meet my educational needs.	Satisfaction 1
						Mobile learning applications are fun for me.	Satisfaction 2
						Mobile learning applications make me happy when dealing with them.	Satisfaction 3
						I think Mobile learning applications help me learn.	Satisfaction 4
Actual use At the ML.							
					Davis (1989) [30], Venkatesh (2003) [31] and DeLone and McLean (2004) [27]	I mainly use mobile learning applications.	Actual use 1
						I already use mobile learning applications regularly.	Actual use 2
						I will use mobile learning applications regularly in the future.	Actual use 3

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