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Article abstract

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Abstract

Although online learning has become ubiquitous worldwide, earlier research has neglected the relationship between its actual use and security concerns. Learners' lack of security awareness while using learning technologies remains rarely studied. This paper integrates Delone and McLean's information system success (D&M-ISS) model with the security triangle framework. Data from 2,451 higher education students at different universities and a wide variety of disciplines in Iraq were collected. In addition to the effectiveness of the D&M-ISS factors, the research findings based on the structural equation model suggest that the three constructs of the security triangle framework—namely, confidentiality, integrity, and availability—were significant predictors of students' use of online learning. This research can thus help academic organizations understand factors that can lead to the successful implementation of online learning and learners' security awareness.

Keywords: online learning, Delone and McLean's information system success model, security triangle framework, higher education

Introduction

Online learning refers to the delivery of educational content and the acquisition of new knowledge and information via the Internet. It allows learners to access learning resources and instructional materials without time and place restrictions. People who face time management issues or have job commitments may find online learning to be a perfect learning environment that can meet their individual needs (Solimeno et al., 2008). However, the absence of direct face-to-face interaction is a major drawback of asynchronous learning (Al-Azawei & Lundqvist, 2015). Other factors that can affect the successful implementation of online learning must also be examined.

Earlier literature has investigated factors that can predict the adoption of online learning (Mshali & Al-Azawei, 2022; Zhang et al., 2020), with little attention paid to learners' awareness of security in adopting and using this learning method. However, the adoption of online learning has grown quickly, and this type of learning requires high levels of privacy and confidentiality. According to El-Khatib et al. (2003), the main focus of e-learning systems has been on course design and development; security and privacy requirements have been neglected. Ameen et al. (2020) confirm that a major challenge is that devices that are used for both personal and work activities can cause various security risks.

To this end, the present research aims to investigate features that could lead to successful implementation of online learning and its use. Though several models have been suggested to examine the successful use and implementation of technology, their key focus has been on determinants of intention to use rather than actual use. According to the theory of reasoned action, people's actions are goal-directed in that they consider the effects of such actions before performing them (Ajzen & Fishbein, 1980). This theory suggests that behavioral intention is a key predictor of actual behavior. Other theories have also been based on this notion (e.g., Davis, 1985; Venkatesh et al., 2003; Venkatesh et al., 2012).

This research considers the role of security concerns in predicting online learning use. It is grounded on the information systems success theory proposed by Delone and McLean (2003). This theory accounts for the role of quality (system quality, information quality, and service quality) in predicting technology success, but it does not include the possible effect of security. According to Maqableh et al. (2021), considering security constructs in understanding technology success is crucial. This research, therefore, represents the first attempt to address this limitation and shed light on the importance of security variables in predicting online learning use. Its results add significant contributions to information systems success in the context of online learning.

Related Work and the Proposed Model

E-Learning in Iraq

To support the implementation of e-learning in Iraq, most Iraqi universities started adopting e-learning technologies in 2010 to create a complementary educational system to traditional face-to-face learning (Al-Azawei et al., 2016). Many outstanding projects have been adopted by the Iraqi Ministry of Higher Education to assist the transition to a digital society and support the implementation of e-learning. The project with the United Nations Educational Scientific and Cultural Organisation (UNESCO) is one example of the integration of e-learning systems in Iraqi higher education (Al-Azawei et al., 2016).

However, with the acceleration of e-learning, some security concerns remain about its exposure to various threats.

In Iraq, cyber improvement has been late, and the foundation of a cyber-security procedure has been severely harmed by decades of war. To develop the country's cybersecurity, Iraqi legislators must upgrade and back the infrastructure by enacting cyber laws. There is still little development or awareness of cybersecurity in Iraq, so Iraqi society is vulnerable to cybercrimes.

The Proposed Model

This research is grounded on Delone and McLean's (2003) information systems success (D&M-ISS) model and the security triangle framework (Stallings, 2003). The available information systems frameworks, such as the technology acceptance model, the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and the D&M-ISS model, have neglected the importance of security in the adoption and/or success of information systems. Accordingly, previous literature has attempted to address this limitation by considering security concerns. For example, Salam and Ali (2020) extended the UTAUT with the three variables of the security triangle framework, namely, confidentiality, integrity, and availability, to investigate cloud computing adoption. These three constructs were proposed as direct predictors of users' behavioral intentions; the findings revealed that perceived availability was the only significant predictor of cloud computing adoption.

Delone and McLean's Information Systems Success Model

In 1992, the first version of Delone and McLean's D&M-ISS model was proposed (Delone & McLean, 1992). It suggests a relationship among six constructs: information quality, system quality, perceived satisfaction, information systems use, user impact, and organizational impact. This model, however, was updated in 2003 with the addition of a new construct: service quality (Delone & McLean, 2003). Previous literature has successfully validated the new model with many applications to information systems (Al-Azawei, 2019; Al-Azawei & Al-Azawi, 2021; Dong et al., 2014).

This model suggests that better system quality can lead to improving system use and user satisfaction, and this, in turn, can enhance users' productivity (Delone & McLean, 2003). Reliability, ease of use, accessibility, and functionality are key identifiers of system quality. Another assumption of this model is that better system objectivity can be achieved with the provision of high-quality information and content. Accordingly, information quality is proposed to influence system use and user satisfaction. This construct can be measured based on information accessibility, accuracy, and timeliness, as well as context and relevancy (Dong et al., 2014). Furthermore, Delone and McLean (2003) suggest that service quality is not a subset of system quality. According to Pitt et al. (1995), service quality refers to the discrepancy between the perceptions of customers and expectations. Thus, service quality in information systems can include the availability of physical facilities, users' ability to perform a particular service dependably, prompt service provision, and support for users if they face any technical issues (Pitt et al., 1995). In higher education, students should be treated as customers; that is, they should be offered high-quality educational services (Al-Adwan et al., 2022).

User satisfaction, on the other hand, covers the perspectives of users about a particular technology or system that could meet their individual information needs (Dong et al., 2014). Behavioral intention is the apparent willingness of users to adopt a particular technology (Alowayr & Al-Azawei, 2021). Delone and McLean (2003) propose that user satisfaction and behavioral intention are associated with actual use. The model assumes that intention to use or behavioral intention and user satisfaction can be highly influenced by information, system, and service quality (Delone & McLean, 2003). These assumptions have been supported in online and e-learning contexts (Al-Adwan et al., 2021; Al-Adwan et al., 2022; Awad et al., 2022; Çelik & Ayaz, 2022). In this study, the following hypotheses were proposed:

H1: Information quality is a predictor of behavioral intention.

H2: Information quality is a predictor of user satisfaction.

H3: System quality is a predictor of behavioral intention.

H4: System quality is a predictor of user satisfaction.

H5: Service quality is a predictor of behavioral intention.

H6: Service quality is a predictor of user satisfaction.

H7: User satisfaction is a predictor of behavioral intention.

H8: Behavioral intention is a predictor of the actual use of online learning.

H9: User satisfaction is a predictor of the actual use of online learning.

Security Triangle Model

Users perceive the importance of security measures because of the illegal practices of hackers. Such activities could be harmful to their privacy and may reveal their personal information in an unauthorized manner (Maqableh et al., 2021). Hence, the security triangle model, one of the most popular security frameworks, characterizes several criteria that each secure system must meet. Three constructs—namely, confidentiality, integrity, and availability—are considered in the use of information systems (Chaeikar et al., 2012). However, few studies have investigated the effect of these three constructs on behavioral intention to use technology (Salam & Ali, 2020) or attitude toward technology use (Meharia, 2012). Hartono et al. (2013) assumes that these factors are predictors of the actual use of e-commerce. Farooq et al. (2020) have examined the prediction ability of the security construct on students' attitudes to adopt e-learning.

In this research, the security triangle constructs were integrated with the D&M-ISS model to examine online learning use. The rationale behind this integration was that users may not use a particular technology if they feel that their individual information will be obtained by an unauthorized party. This extension represents the key contribution of this study as earlier research paid too much attention to identifying predictors of behavioral intention only (Ajzen & Fishbein, 1980; Davis, 1986). Accordingly, between 30% and 45% of the variance of actual use has previously been explained (Alshurideh et al., 2020; Isaac et al., 2019). This research, therefore, aims at improving the explained variance of online learning's actual use by investigating the effect of the security triangle framework.

Confidentiality. Confidentiality refers to the prevention of unauthorized people from capturing, interpreting, or understanding information (Tsiakis & Sthephanides, 2005). Confidentiality is fulfilled by using a particular approach to change the form of data in a manner so that it is not understandable by an unauthorized party. E-learning security requires the protection of users' information by preventing unauthorized users from reaching a system's information and data. In this research, we proposed that confidentiality is a direct predictor of online learning's actual use. This is based on the assumption that if learners know that their personal information is accessed by an authorized party, the online learning system will not be used. Hence, the following hypothesis is assumed:

H10: Perceived confidentiality is a predictor of the actual use of online learning.

Integrity. Integrity guarantees that users' information has not been modified in any unapproved manner (Stallings, 2003). The integrity of information should be maintained at its creation, transmission, and storage. Changing information incorporates inclusion, erasure, and substitution breaches. In the e-learning sector, users should ensure the ability to keep their information without any modifications. Moreover, learning contents and other system materials should only be modified by authorized users. At the same time, such resources should be maintained so that no tampering or revision can be done illegally. Accordingly, it was assumed here that illegal modifications, whether on users' personal information or learning content, can negatively affect the actual use of online learning technology.

H11: Perceived integrity is a predictor of the actual use of online learning.

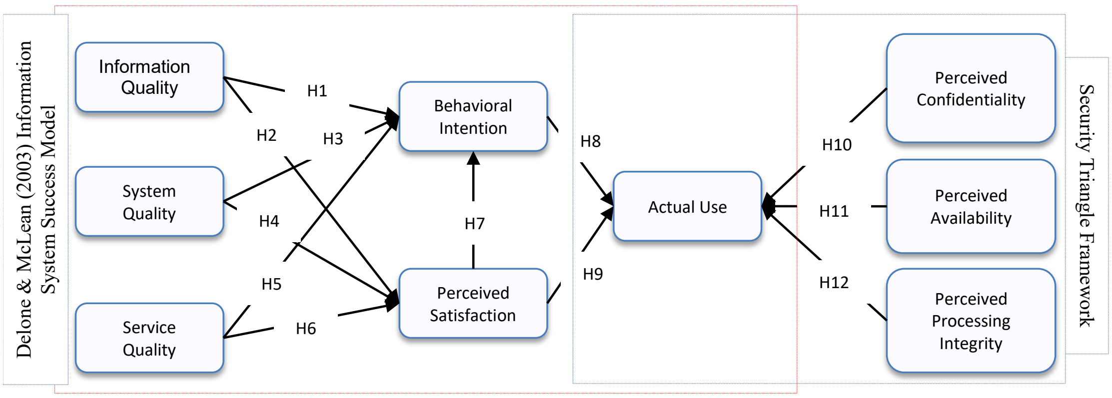
Availability. Availability of information at any time, from any place, and only for authorized people is one of the most important priorities of any system such as an educational platform. Many actions can be performed to ensure information availability. These may include but are not limited to maintaining the operating system's environment, ensuring that a system is free of errors, continuously reviewing a system's updates to avoid interruption of services, and storing backup data to help recover lost data and avoid losing data due to unforeseen incidents. E-learning security requires authorized users' ability to access learning resources at any time. As such, the following hypothesis was assumed:

H12: Perceived availability is a predictor of the actual use of online learning.

Figure 1 depicts the proposed model.

Figure 1

The Proposed Research Model



Research Methods

The Research Design Method and Survey

The quantitative research design method was adopted in this study as it uses a questionnaire approach to collect data. This method was chosen as a suitable technique for understanding the association among the proposed model factors and for supporting or rejecting the research hypotheses. Overall, nine variables were measured using 36 closed-ended questions. In this research, the questionnaire items were adapted from previously validated scales (Al-Azawei, 2019; Al-Azawei & Lundqvist, 2015; Alowayr & Al-Azawei, 2021; Isaac et al., 2019; Meharia, 2012; Ramirez-Correa et al., 2017). However, some items were modified to fit the study's context. All items were designed based on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Although all items were designed in English, they were translated into Arabic for participants' ease of understanding. The translations were checked by all authors—all speakers of both Arabic and English—to ensure clarity and accuracy. Accordingly, the authors provided individual feedback on the survey, and this in turn led to a few changes made to some questions.

Participants and Context

Educational institutions in Iraq use online learning platforms to deliver learning content and communicate with students. Moodle and Google Classroom have been the most adopted platforms due to their reliability. This research targeted higher education students at public and private universities in Iraq who adopted the online learning approach. Students were from different universities, which were allocated in several governorates from south to north Iraq. Moreover, the respondents were from several different disciplines and departments, including the humanities, sciences, engineering, and medicine.

The authors distributed a link to the questionnaire to lecturers at different universities. They in turn distributed it to their students. Accordingly, the probabilistic random sampling technique was adopted as each higher education student from the selected universities could participate in this research. This is an effective method in quantitative research design: it is commonly linked with survey research techniques, researchers can make inferences from the sample about a whole population, and this technique produces unbiased data (Saunders et al., 2012). Table 1 shows the demographic information of the research participants.

Table 1

Demographic Information of the Research Participants (n = 2,451)

Demographic information	*n*	%
Gender		
- Female	1,374	56.1
- Male	1,077	43.9
Age group		
- 18–20	659	26.9
- 21–23	1,135	46.3
- 24–26	325	13.3
- 27–29	102	4.2
- 30+	230	9.4
Experience with online learning		
- High experience	559	22.8
- Moderate experience	1,892	77.2
Do you have a smartphone or computer?		
- No	194	7.9
- Yes	2,257	92.1
Do you have Internet service either at home or via mobile?		
- No	337	13.7
- Yes	2,114	86.3

Data Collection

The survey was distributed online via social media applications such as Facebook Messenger, Viber, and WhatsApp. Overall, 2,451 valid responses were received. A large sample size can reduce the error rate in generalizing the research findings (Saunders et al., 2012). According to Lowry and Gaskin (2014), the number of cases required for the use of a structural equation model can be identified by two methods. The first is that the smallest sample size can be calculated by 10 multiplied by the largest number of constructs used to predict a particular variable. The other method suggests setting the statistical power of regression at 80% and the probability value of significance at .05. Based on both methods, the sample size used in this research was adequate.

Data Analysis Techniques

The data collected in this research were analyzed using SmartPLS version 3.0 (Ringle et al., 2015) and SPSS version 21. Validating the instrument properties and measuring the cause-and-effect associations among the proposed research model constructs were performed using SmartPLS, whereas frequencies were calculated using SPSS.

Results

Descriptive Statistics

Table 2 shows that the mean scores of the research constructs are higher than the midpoint of 2.5. The standard deviation, on the other hand, ranged from 0.913 to 1.154, indicating that values were moderately spread around the mean. Furthermore, skewness and kurtosis confirmed that data were approximately normally distributed as their values were less than 3 and greater than −3, as recommended by Peat and Barton (2005). As recommended by Pallant (2013), tolerance values were higher than 0.10 and variance inflation factors values were less than 10, confirming that the multicollinearity assumption was supported.

Table 2

Descriptive Statistics

Factor	Min.	Max.	*M*	*SD*	Skewness	Kurtosis	Tolerance	VIF
BI	1.00	5.00	2.795	1.203	0.045	−1.088	0.253	3.950
PS	1.00	5.00	3.026	1.154	−0.225	−0.908	0.228	4.388
IQ	1.00	5.00	2.956	1.112	−0.120	−0.813	0.231	4.338
SQ	1.00	5.00	2.880	1.070	−0.083	−0.752	0.179	5.586
SerQ	1.00	5.00	3.277	1.062	−0.538	−0.334	0.291	3.442
AU	1.00	5.00	3.084	0.974	−0.418	−0.251	0.428	2.336
PC	1.00	5.00	3.303	1.074	−0.627	−0.246	0.428	2.336
PA	1.00	5.00	3.083	1.101	−0.276	−0.736	0.586	1.708
PI	1.00	5.00	3.339	0.913	−0.937	0.884	0.393	2.547

Note. VIF = variance inflation factors; BI = behavioral intention; PS = perceived satisfaction; IQ = information quality; SQ = system quality; SerQ = service quality; AU = actual use; PC = perceived confidentiality; PA = perceived availability; PI = perceived processing integrity

Psychometric Properties of the Research Questionnaire

First, the questionnaire properties were validated. The outer loadings of all items were more than 0.7 (see Appendix A). Moreover, the instrument's reliability was established, as shown in Table 3. Cronbach's coefficient alpha represents a measurement of the reliability of a research questionnaire in which ≥ 0.7 is an acceptable threshold (Pallant, 2013). The questionnaire's convergent validity was confirmed. This can be established if the values of composite reliability and average variance extracted exceed 0.7 and 0.5, respectively (Hair et al., 2006). Finally, discriminant validity was also confirmed as the variance shared between one variable and another construct was less than the variance shared by a variable with its constructs (Fornell & Larcker, 1981). Table 4 presents confirmation of the discriminant validity.

Table 3

Construct Reliability and Validity

Factor	Cronbach's α	Rho_A	Composite reliability	AVE
AU	0.838	0.860	0.893	0.681
BI	0.942	0.942	0.958	0.851
IQ	0.927	0.927	0.945	0.773
PA	0.874	0.883	0.913	0.724
PC	0.938	0.939	0.956	0.843
PI	0.877	0.878	0.916	0.731
PS	0.889	0.892	0.931	0.818
SerQ	0.836	0.839	0.901	0.753
SQ	0.903	0.906	0.928	0.721

Note. AVE = average variance extracted; AU = actual use; BI = behavioral intention; IQ = information quality; PA = perceived availability; PC = perceived confidentiality; PI = perceived processing integrity; PS = perceived satisfaction; SerQ = service quality; SQ = system quality

Table 4

Discriminant Validity (Fornell–Larcker Criterion)

Factor	AU	BI	IQ	PA	PC	PI	PS	SerQ	SQ
AU	0.825								
BI	0.709	0.922							
IQ	0.734	0.761	0.879						
PA	0.513	0.432	0.496	0.851					
PC	0.634	0.532	0.607	0.528	0.918				
PI	0.634	0.515	0.561	0.650	0.687	0.855			
PS	0.721	0.842	0.786	0.453	0.578	0.559	0.904		
SerQ	0.724	0.688	0.751	0.513	0.641	0.637	0.725	0.868	
SQ	0.753	0.781	0.854	0.511	0.650	0.607	0.788	0.814	0.849

Note. AU = actual use; BI = behavioral intention; IQ = information quality; PA = perceived availability; PC = perceived confidentiality; PI = perceived processing integrity; PS = perceived satisfaction; SerQ = service quality; SQ = system quality

Table 5 shows discriminant validity based on the Heterotrait–Monotrait ratio (HTMT). Henseler et al. (2015) state that the HTMT should be < 1, but there is still a debate regarding its exact acceptable threshold. HTMT values may indicate a lack of discriminant validity if they are close to 1 (Ab Hamid et al., 2017). Henseler et al. (2015) state that HTMT values of 0.85 or 0.90 are acceptable. In this research, the HTMT values between system quality and information quality as well as system quality and service quality are about 0.93. This is because the three constructs measure quality from different angles, so there is an obvious correlation among them. Roemer et al. (2021) demonstrate that HTMT may generate biased estimations of the correlations between constructs. According to Rönkkö and Cho (2022, p. 33), "a large correlation does not always mean a discriminant validity problem if one is expected based on theory or prior empirical observations." Thus, the instrument properties are supported.

Table 5

Discriminant Validity (HTMT)

Factor	AU	BI	IQ	PA	PC	PI	PS	SerQ
BI	0.792							
IQ	0.830	0.814						
PA	0.586	0.464	0.540					
PC	0.714	0.566	0.652	0.569				
PI	0.744	0.566	0.624	0.721	0.758			
PS	0.829	0.918	0.865	0.500	0.632	0.633		
SerQ	0.862	0.773	0.851	0.582	0.723	0.743	0.839	
SQ	0.860	0.846	0.931	0.563	0.710	0.684	0.877	0.935

Note. HTMT = Heterotrait–Monotrait ratio; AU = actual use; BI = behavioral intention; IQ = information quality; PA = perceived availability; PC = perceived confidentiality; PI = perceived processing integrity; PS = perceived satisfaction; SerQ = service quality; SQ = system quality

Results of the Original Model

Table 6 and Figure 2 indicate that all original hypotheses of the D&M-ISS model were supported except for H5. The model explained 0.748, 0.679, and 0.557 of the variance of behavioral intention, perceived satisfaction, and actual use, respectively.

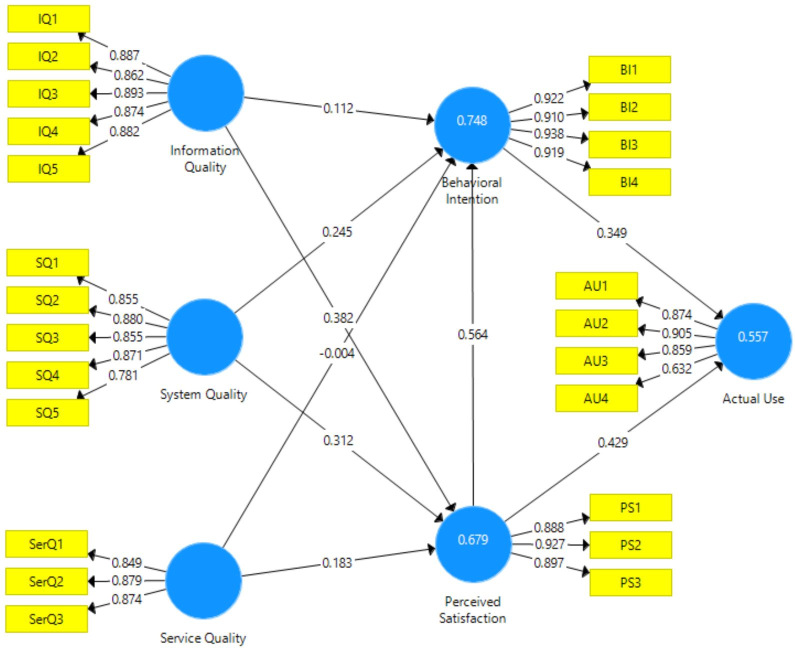
Table 6

Findings Without the Security Triangle Constructs

Hypothesis	β	*t*	*p*	Findings
H1: information quality → behavioral intention	0.112	4.346	< .001	Supported
H2: information quality → perceived satisfaction	0.382	13.908	< .001	Supported
H3: system quality → behavioral intention	0.245	8.814	< .001	Supported
H4: system quality → perceived satisfaction	0.312	9.604	< .001	Supported
H5: service quality → behavioral intention	−0.004	0.222	.824	Rejected
H6: service quality → perceived satisfaction	0.183	7.618	< .001	Supported
H7: perceived satisfaction → behavioral intention	0.564	27.145	< .001	Supported
H8: behavioral intention → actual use	0.349	12.381	< .001	Supported
H9: perceived satisfaction → actual use	0.429	14.653	< .001	Supported

Figure 2

The Model Without the Security Triangle Constructs



Note. IQ = information quality; BI = behavioral intention; SQ = system quality; AU = actual use; PS = perceived satisfaction; SerQ = service quality

Results of the Proposed Model

Table 7 and Figure 3 depict the key findings of the proposed hypotheses. Eleven out of twelve hypotheses were confirmed. The R^2 explained by the independent variables of the proposed model for the three dependent constructs of behavioral intention, perceived satisfaction, and actual use were 0.748, 0.679, and 0.642, respectively.

Three constructs were predictors of behavioral intention: information quality ($\beta_{IQ \rightarrow BI} = 0.112$, $p < .001$), system quality ($\beta_{SQ \rightarrow BI} = 0.245$, $p < .001$), and perceived satisfaction ($\beta_{PS \rightarrow BI} = 0.564$, $p < .001$). Service quality ($\beta_{SerQ \rightarrow BI} = -0.004$, $p = .822$), on the other hand, was not a significant determinant of behavioral intention, whereas information quality ($\beta_{IQ \rightarrow PS} = 0.382$, $p < .001$), service quality ($\beta_{SerQ \rightarrow PS} = 0.183$, $p < .001$), and system quality ($\beta_{SQ \rightarrow PS} = 0.312$, $p < .001$) were determinants of perceived satisfaction.

Behavioral intention ($\beta_{BI \rightarrow AU} = 0.281$, $p < .001$) and perceived satisfaction ($\beta_{PS \rightarrow AU} = 0.249$, $p < .001$) were predictors of actual use. This study also confirms that the key constructs of the security triangle model, namely, perceived confidentiality ($\beta_{PC \rightarrow AU} = 0.180$, $p < .001$), perceived availability ($\beta_{PA \rightarrow AU} = 0.063$, $p = .001$), and perceived processing integrity ($\beta_{PI \rightarrow AU} = 0.186$, $p < .001$), were significant determinants of online learning actual use.

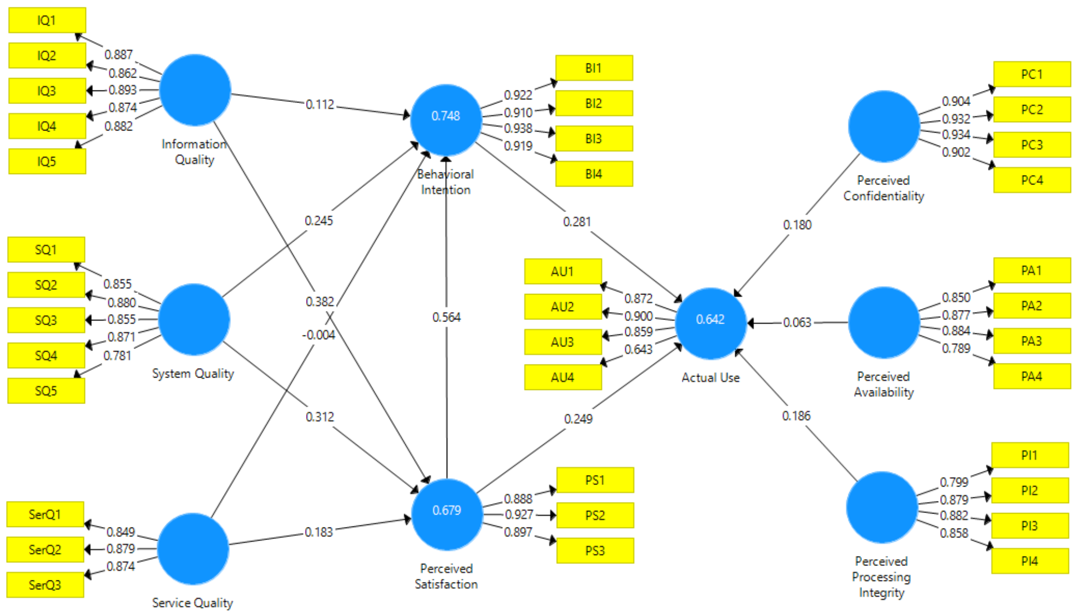
Table 7

The Proposed Research Model Findings

Hypothesis	β	*t*	*p*	Findings
H1: information quality → behavioral intention	0.112	4.338	< .001	Supported
H2: information quality → perceived satisfaction	0.382	13.875	< .001	Supported
H3: system quality → behavioral intention	0.245	8.866	< .001	Supported
H4: system quality → perceived satisfaction	0.312	9.485	< .001	Supported
H5: service quality → behavioral intention	−0.004	0.225	.822	Rejected
H6: service quality → perceived satisfaction	0.183	7.534	< .001	Supported
H7: perceived satisfaction → behavioral intention	0.564	26.876	< .001	Supported
H8: behavioral intention → actual use	0.281	10.991	< .001	Supported
H9: perceived satisfaction → actual use	0.249	8.789	< .001	Supported
H10: perceived confidentiality → actual use	0.180	8.073	< .001	Supported
H11: perceived availability → actual use	0.063	3.477	< .01	Supported
H12: perceived processing integrity → actual use	0.186	7.682	< .001	Supported

Figure 3

The Proposed Research Model Findings



Note. IQ = information quality; BI = behavioral intention; PC = perceived confidentiality; SQ = system quality; AU = actual use; PA = perceived availability; SerQ = service quality; PS = perceived satisfaction; PI = perceived processing integrity

Discussion

This study sought to investigate the effect of security triangle variables on the actual use of online learning. The modified model (Figure 3) was compared with the original model (Figure 2) in terms of the change in R^2 for actual use. This modification shows that the integration of the three security triangle constructs helps improve the explanation of the variance of online learning actual use from 0.557 in the original model to 0.642 in the modified model.

Information quality was a significant predictor of behavioral intention and student satisfaction to support the findings of other studies (Al-Azawei, 2019; Al-shargabi et al., 2021; Ramirez-Correa et al., 2017; Shim & Sug Jo, 2020). This means that the quality of the provided information on e-learning technology has a direct and significant effect on technology acceptance and user satisfaction. As information quality consists of information accessibility, accuracy, timeliness, and relevancy (Dong et al., 2014), the research findings suggest that the system's available information was of a high standard and quality. This may also indicate that the information provided by the online learning system was very informative.

The effect of system quality on user satisfaction and technology adoption was also supported in this research. On the other hand, Shim and Sug Jo (2020) suggest that in their study, system quality was a determinant of neither behavioral intention nor perceived satisfaction of e-learning technology. In our research, however, the investigated educational technology had standard features such as reliability, accessibility, and usability. Reliability refers to the existence of a system that users can use to achieve their needs without too many technical problems or malfunctions. As mentioned, Iraqi higher education institutions have implemented either Moodle or Google Classroom as learning management systems. Both have high-quality maintenance, improvement, and upkeep. Moreover, the educational technologies used were accessible from any location and at any time as universities have either used their own servers or relied on Google Classroom servers, which provide more reliability and service stability. Usability refers to the ease of performing educational tasks or communicating effectively on the university learning management systems (Shim & Sug Jo, 2020). The adopted learning technologies were usable as students used them for at least four months before collecting the research data. This is more apparent in Google Classroom as it has high usability standards (Harefa, 2020).

In online learning, service quality means learners' perceptions of who will provide technical support and to perform a service dependably. In this research, service quality had a significant effect on user satisfaction, but it was not a predictor of behavioral intention. Previous research shows contradictory findings (Petter & McLean, 2009; Ramirez-Correa et al., 2017). The rationale for our results is that students were willing to use online learning, so they were not too concerned about technical support. However, their satisfaction with online learning could be enhanced if they know who is available to address their technical issues.

The research findings indicated that behavioral intention, perceived satisfaction, perceived confidentiality, perceived availability, and perceived processing integrity were significant determinants of actual use of online learning. In agreement with the D&M-ISS model assumptions (Delone & McLean, 2003), both behavioral intention and perceived satisfaction were determinants of actual use. This indicates that students may not use educational technology when their willingness to adopt it is low. On the contrary, Zhang et al.'s (2020) empirical analyses suggest that behavioral intention did not significantly affect actual e-learning use. This was interpreted to be based on two possible reasons. The former is that students can find important learning content on different Websites and are not limited to their institution's system. The latter is that regardless of their individual willingness, students had to use the university's system as a part of their courses. However, students' dissatisfaction with technology indicates that they are not pleased with its services and it does not meet their needs (Cidral et al., 2020).

This research suggests that the three factors of the security triangle model are predictors of students' actual use of online learning. The cause-and-effect associations between these constructs have been empirically validated. To the best of our knowledge, this has not been investigated in earlier literature. Although these hypotheses have been newly suggested in this research, our overall findings are consistent with those of previous research on e-learning (Farooq et al., 2020), cloud computing adoption (Salam & Ali, 2020), and e-commerce use (Hartono et al., 2013). Our results indicate that hiding students' information from unauthorized entities (i.e., confidentiality) was a determinant of actual use of online learning. Integrity in online learning means guaranteeing that students' information or learning content will not be changed or modified without their permission. Our assumption is that illegal changes made to either students' personal information or learning content can lead to students not using online learning. Our empirical results also confirm that the learning platforms used were available to students because they were maintained regularly, reviewed and updated continuously, and free of errors.

Information quality, system quality, and service quality explained 74.8% and 67.9% of the variance of behavioral intention and perceived satisfaction of online learning success, respectively. This should encourage further focus on all aspects of quality to ensure the successful implementation of such technologies. This research confirms that the quality of online systems, learning content, and services had a significant impact on online learning success, whether in the form of learners' intention to use or learners' satisfaction. Moreover, the security triangle factors' significant influence on actual use of online learning means that security concerns cannot be neglected in considering a technology's success. Students therefore might attribute their success in online learning use to the level of security that the system provides.

Finally, a strength of this study is its inclusion of students from public and private universities, several different governorates, and a wide range of disciplines, reflecting a broad spectrum of Iraqi higher education students. Thus, this study extends the current understanding of online learning usage and success among higher education students by confirming the critical role of security awareness in technology use.

We can draw some practical outcomes from these implications. Higher education institutions need to pay more attention to learning technologies to choose high-quality systems. Learning content should also be updated frequently. The educational content must be in harmony with scientific development and new research discoveries so students feel that they are not left behind. Additionally, technical support should be provided to address any issues students may face with technology. Higher education institutions should also consider security concerns as students are less likely to use technology with possible security risks such as theft or alteration to their personal information. Notably, online learning systems include exam questions and students' grades, so high security is essential for such systems. Therefore, system managers need to maintain learners' privacy to increase their levels of actual use of online learning. This can include protecting learners' private information and prohibiting unauthorized information disclosures.

Conclusion

This study aimed to integrate the security triangle variables (Stallings, 2003) with the D&M-ISS model (Delone & McLean, 2003) to understand their role in predicting the actual use of online learning. Overall, the research showed good results where the variance explained of the dependent constructs was 74.8%, 67.9%, and 64.2% of behavioral intention, perceived satisfaction, and actual use of online learning, respectively. This research was a step in a new direction in identifying factors that may affect the actual use of technology.

Although many significant outcomes were drawn, the research is not without limitations. First, the sample was from Iraq's higher education only, so further research could be conducted in other countries. Second, this study was grounded on the D&M-ISS model, whereas incorporating other technology success theories and security variables may explain the rest of the dependent variables' variance that was not predicted in this research. Third, this study considered the perceptions of students only, whereas accounting for the perceptions of academic staff is a substantial part of the successful implementation of learning technology. Fourth, although the translation of the research questionnaire was checked by experts, back translation was not conducted. Finally, the analysis was based on structural equation modeling, while building a classification model may open the door for further analysis. Such limitations may invite further research to be conducted.

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Appendix A

The Research Questionnaire

Factor	Outer loading	Reference
Behavioral intention (BI)		
BI1: I intend to use the online learning system in the future.	0.922	Alowayr & Al-Azawei (2021)
BI2: I will always try to use an online learning system in my daily study.	0.910	
BI3: I plan to use the online learning system in the future.	0.938	
BI4: I will recommend other students to use online learning.	0.919	
Perceived satisfaction (PS):		
PS1: I am satisfied with using the online learning system as a learning-assisted tool.	0.888	Al-Azawei & Lundqvist (2015)
PS2: I am satisfied with using online learning systems' functions.	0.927	
PS3: I am satisfied with my decision to study via the Internet.	0.897	
Information quality (IQ)		
IQ1: The online learning system provides information that is exactly what I need.	0.887	Ramirez-Correa et al. (2017)
IQ2: The online learning system provides information that is relevant to my study.	0.862	
IQ3: The online learning system provides sufficient information.	0.893	
IQ4: The online learning system provides information that is easy to understand.	0.874	
IQ5: The online learning system provides up-to-date information.	0.882	
System quality (SQ)		

SQ1: The online learning system provides interactive features between learners and the system.	0.855	Ramirez-Correa et al. (2017)
SQ2: The online learning system has attractive features to appeal to the learners.	0.880	
SQ3: The online learning system provides high-speed information access.	0.855	
SQ4: The online learning system has flexible features.	0.871	
SQ5: The online learning system is a secure system.	0.781	
Service quality (SerQ)		
SerQ1: I could use the online learning services at any time, anywhere I want.	0.849	Isaac et al. (2019)
SerQ2: The online learning system offers multimedia (audio, video, and text) types of course content.	0.879	
SerQ3: The online learning system enables interactive communication.	0.874	
Actual use (AU)		
AU1: I frequently use the online learning system in my study.	0.872	Al-Azawei (2019)
AU2: I depend upon the online learning system in my study.	0.900	
AU3: I use the online learning system daily.	0.859	
AU4: I use the online learning system often.	0.643	
Perceived confidentiality (PC)		
PC1: I believe my personal information is being properly protected in the online learning system.	0.904	Meharia (2012)
PC2: I believe my personal and behavioral information is properly protected against unauthorized access by the use of user IDs and passwords in the online learning system.	0.932	
PC3: I believe my personal information is stored in a secure and encrypted database in the online learning system.	0.934	

PC4: I believe my personal information is not being exposed to an unauthorized third party in the online learning system.	0.902	
Perceived availability (PA)		
PA1: The risk of interruption of service due to purely technical issues (e.g., a malfunctioning part of a computer or communications device) is high when using the online learning system.	0.850	Meharia (2012)
PA2: The risk of interruption of service due to purely natural phenomena (e.g., wind or water) is high when using the online learning system.	0.877	
PA3: The risk of interruption of service due to human causes (accidental or deliberate) is high when using the online learning system.	0.884	
PA4: The risk of interruption of service due to changes will be communicated to management and users who will be affected when using the online learning system.	0.789	
Perceived integrity (PI)		
PI1: I believe that entering into the online learning system has not been changed inappropriately, whether by accident or deliberately maligned activity.	0.799	Meharia (2012)
PI2: I believe that the data displayed in the online learning system actually came from an authorized person or entity, rather than an imposter.	0.879	
PI3: I believe that the data that were transmitted or entered into the online learning system were not corrupted.	0.882	
PI4: I believe that errors, omissions, breaches of online learning system security, and submissions of complaints will be communicated to authorized users.	0.858	