Assessing the Success rate of e-Learning Systems Aadoption in Saudi Higher Education Institutions during COVID-19 Pandemic: Student Perspective

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Summary
In response to the significant COVID-19 outbreak, countries have enforced the use of E-learning systems as an alternative to traditional learning; to contain the virus and minimize the infection rate while maintaining the continuity of the learning experience. However, the effective adoption of E-learning systems requires a well-understanding of critical factors, especially in times of crisis. In this regard, this study intends to assess the success of the E-learning system adoption by Higher Education Institutions (HEIs) during the crisis of COVID-19 by utilizing the Information Systems Success (ISS) model. This study's adopted model consists of nine interdependent dimensions, namely: Technical System Quality, Information Quality, Service Quality, Learner Quality, Perceived Satisfaction, Perceived Usefulness, System Use, Intention to Use, and System Success. An electronic survey was distributed among higher education students from different universities in Saudi Arabia to explore each model's dimension. Structural Equation Modeling (SEM) has been applied via SmartPLS software to test the causal relationships between dimensions. This study's main results revealed that students' Service Quality, Learner Quality, and the Intention to Use by students are essential drives for E-learning System Use during the Covid-19 pandemic. Meanwhile, the Intention to Use the system is significantly influenced by Perceived Satisfaction and Perceived Usefulness dimensions. Further, Perceived Satisfaction, Perceived Usefulness, and System Use are interdependent, and all three have a significant positive impact on E-learning System Success.
Keywords:
COVID-19; e-learning systems; higher education; Information Systems Success (ISS) model; institutions.

1. Introduction

The significant spread of COVID – 19, which occurred in December of 2019, caused the World Health Organization (WHO) to announce the disease as a global pandemic [1]. The highly infectious nature of the virus through the respiratory emission of droplets into the air or onto solid surfaces, and the high rate of daily mortality cases, have issued a global change in the nature of procedures and policies. Over 130 governments placed preventive laws like quarantine laws, social distancing, off-site employment, and distanced learning as counteracting measures to contain the virus and reduce the high infection rate [2].

Education is considered an integral part of advancing as a nation [3]. Placing forced quarantine directly impacted the populations' education process, as 185 countries closed off schools and Higher Education Institutions (HEIs) [2]. Several education institutions adapted to the circumstances by harnessing modern technologies, where a high migration to the E-learning methodology was witnessed during the spread of COVID – 19. According to a recent report published by UNESCO, around half a billion higher education students have used Learning Management Systems (LMS) tools as the main platform for receiving education [2].

The E-learning system is considered the offshore alternative of traditional education, providing online live course delivery, knowledge assessment tools, and an overall collaborative environment [4, 5]. Educationalists can share course materials in different media forms, including PowerPoint, PDF, and Word sheets through social media communication platforms or E-learning systems adopted by HEIs. Access to such platforms enables the maximum reach of content to students.

However, the sudden high rate conversion to E-learning systems during the crisis of COVID-19 resulted in the raised appearance of many challenges like internet connectivity issues, insufficient online resources, and the lack of efficient IT support, and high traffic that lead to a platform overload [6]. These challenges may lead to E-learning education's failure combined with the improper management process that includes system observation and resource allocation [7]. In this regard, the proper adaptation of E-learning systems and the ongoing system efficiency evaluation are critical to ensure the E-learning education process [6, 8]

Due to the multi-dimensional nature of the E-learning environment that combines computer and information science, psychology, and educational studies, researchers and scholars focused on evaluating efficiency from multiple aspects. For example, focusing on the evaluation aspect of hardware technologies [9] and examining the efficiency of student assessment within the E-learning approach [10-14]. Another study by [8, 15] investigated LMS evaluation on multi-dimensional based on students' view.

Despite the significant contributions founded in the literature regarding the context of -learning evaluation, there is a lack of works regarding the assessment of E-learning systems adoption during the crisis of COVID-19. Therefore, this paper aims to assess the success rate of E-learning systems adoption by HIEs during the COVID-19 pandemic within the premises of the Kingdom of Saudi Arabia. This study will adopt the updated Information Systems Success (ISS) model proposed by DeLone and McLean as a theoretical foundation to determine the main factors responsible for the E-learning systems' success. This model is built based on the interrelationships between nine dimensions: Technical System Quality, Information Quality, Service Quality, Learner Quality, Perceived Satisfaction, Perceived Usefulness, System Use, Intention to Use, and System Success. An electronic

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survey will be distributed among higher education students from different Saudi universities to explore their perspective towards each dimension of E-learning systems success. Based on received responses, the Structural Equation Modelling (SEM) will be applied via SmartPLS software to test the relationships between the model constructs.

The remainder of the paper is structured as follows: to build a well enough knowledge base, a literature review is conducted covering the general studies and concepts related to the E-learning systems and D&M IS Success model (Section 2). The research methodology is providing details about the used model and its dimensions alongside the proposed hypotheses (Section 3). The next (Section 4) displays the retrieved results regarding the measurement and structural models. A discussion of these results (Section 5) will simplify the found results by matching them to the acceptance or rejection of the proposed hypotheses. Following (Section 6), which provides practical implications that can be utilized by educational institutions and countries. To end, the conclusion (Section 7) summarizes all previous sections.

2. Literature Review

2.1 E-Learning and E-learning systems

As a result of the technological advancement in the mid-90s, namely the spread of internet access points and the availability of laptops and hand-held devices, higher opportunities were generated for E-learning to be adapted by various organizations [16]. E-learning has been defined by [17] as "the delivery of training and education via networked interactivity and a range of other knowledge collection and distribution technologies." In a book published by [4], E-learning divided into two main types, namely: synchronous learning and asynchronous learning. Synchronous learning is described as real-time courses with direct communication and instructor led. In contrast, asynchronous learning is considered time-independent systems to complete the courses based on the learner's preferred time. E-learning is a full-featured, powerful tool with cost-effectiveness, high accessibility to numerous materials, and flexible with no time or graphical restrictions [4].

In recent years, Information and Communication Technologies (ICT) has enhanced the E-learning systems by integrating advanced tools and technologies into Higher Education Institutions HEIs. Students and HEIs are experiencing a new era of transition and rapid transformation into the E-learning systems. This shift from traditional learning to the E-learning systems is quite challenging and complicated [18].

According to a recent study, the lack of an appropriate learning environment, technological skills, and Internet connection issues negatively impact E-learning effectiveness during the COVID-19 pandemic.

Another study was conducted to investigate students' acceptance of e-learning systems [19]. It proposed a model to determine key influencing factors that affect students' acceptance of the e-learning system. The results indicated that the system's quality and the ability to share knowledge through the E-learning system significantly affect students' acceptance of the system.

Moreover, [6] referred to students' challenges within the E-learning environment, including psychological concerns, such as stress, depression, anxiety, and technicality issues like connectivity problems. The study also indicated the effect of the absence of a convenient environment in the pandemic duration.

2.2 DeLone and McLean (D&M) IS Success model

To study the degree of efficiency of E-learning system implementation in HEIs, this work uses the Information System Success (ISS) model, also known as the DeLone and McLean (D&M) IS Success model [20]. The initially proposed model in 1992, primarily focused on conceptualizing an information system success study framework that relied on the dependency relation between dimensions [20]. The original proposition consisted of six interdependent dimensions of success, which are: System Quality, Information Quality, System Use, User Satisfaction, Individual impact, and Organizational impact. The dependency between the dimensions is structured so that the System Quality and Information Quality would simultaneously affect the Use and User Satisfaction dimensions while being independent of each other. In turn, the Use and User Satisfaction dimension would be interchangeably dependent on each other, as they can positively or negatively affect each other. These two dimensions directly affect the Individual impact dimension, which in turn leads to a direct impact on the organization. Figure 1 represents the D&M initial ISS model with the dependency relations among dimensions.

The proof of the original research's importance was made evident by the subsequent studies that applied and extended the model. Whether it viewed the negative, positive aspects or deliberating on the challenges that might be faced. Some cases, studies focused on articulating a further development study and delivering insight into the model's validity. A research study [21] produced empirical results to validate the sequence of dependency on the three dimensions, which are System Quality, Information Quality, and Usefulness. It also raised a discussion point of the proper dependency factor of impact on Use, arguing that it does not directly affect but simply precedes the variable.

Further on the topic of the impact of the D&M model is the frequent citation by different articles across many information systems journals. To mention, according to [22], the [20] article was the top-cited literature work in the time frame of 1990 -2004 within the IS publications domain. The article was also subjected to a broad spectrum of empirical studies investigating the different dependencies between dimensions, providing validating model results [23]. Moreover, 14 reviews were taken into consideration to produce the revised model [20] in response to the technological advancement and the major role change of Information Systems throughout the following decade of the original model and the viable studies that produced valuable insights.

[20] suggested an update to the model by adding a new dimension called Service Quality. Combining the Individual impact and the Organizational impact into a singular dimension named Net Benefits, presented by figure 2. The addition of Service Quality is a direct result of a transformation in information systems' responsibilities to the dual providing of information and services. The adjustment is also supported by several studies, for example [24], which mentions that the individual consideration of product quality would lead to invalid results. As a result, of the continuous evolution of IS implementations, the systems' impact surpassed the direct user. Studies have suggested the inclusion of multiple parties to be taken into account depending on the study's environment. In response to that [20] collapsed the Individual and Organization impact into the Net Benefits dimension.

2.3 ISS model in the context of E-learning systems

It is argued that the updated ISS model is well-aligned with measuring the success of the web-based systems [20]. In this regard, most E-learning studies have applied and extended the updated model to identify E-learning adoption success determinants. These studies were built on the D&M updated model's original premise states that System Quality and Information Quality are determinants of the System Use and User Satisfaction affecting the System Success. For example, [26] presented a model for evaluating a Learning Management System (LMS) implemented in HEI of Sub-Saharan countries by modifying D&M model constructs' names to suit the E-learning evaluation context. The study concluded that student satisfaction is not influenced significantly by the quality of the system and the quality of services since the course quality was the exclusive determinant of user satisfaction. Otherwise, [27] utilized the model to assess the success of an E-learning system called Online Instructor Suite (OIS). It revealed both system quality and information quality have a significant impact on user satisfaction and system use. The results also indicated at the user satisfaction construct has a substantial effect on system's ultimate success more than the impact explained by the system use construct.

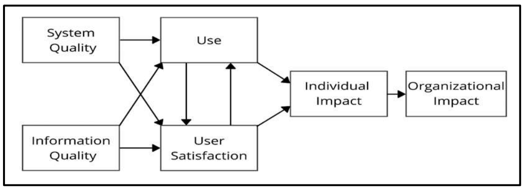

Figure 1: DeLone & McLean 1996 ISS model [25]

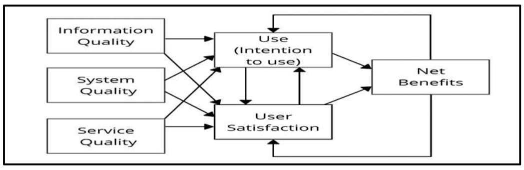

Figure 2 The Reformulated ISS model [20].

Besides, [28] conducted a study concerned with the impact of quality factors on the learners' intention to use the E-learning system. As a result, a new construct known as instructor quality was introduced, significantly influencing the user's E-learning acceptance. It empirically asserted that quality factors, including information quality, service quality, system quality, and instructor quality, are considered significant determinants for user perception towards an E-learning system. In agreement with the previous study, [10] confirmed that instructor quality, as one of seven proposed quality antecedents, has a primary role in increasing students' satisfaction with the E-learning system.

To determine the critical factors that affect the students' continuance intention to use the e-learning systems, [29] replaced the 'net benefits' construct with the 'continuous intention of using the E-learning system' construct and the 'system usage' with 'perceived value' construct. It demonstrated that the quality antecedents significantly affect the perceived value and user satisfaction, affecting students' continuance intentions of using e-learning systems. In the same context, [30] conducted a study to investigate the role of user satisfaction in the relationship between perceived value and continuance intention. It confirmed that user satisfaction is an integral part of the association between perceived value and continuance intention to use the E-learning system.
On the other side, [31] assessed the effect of students' cultural characteristics, like individualism and collectivism, on E-learning systems success. The study verified the primary role of the cultural dimension on the perceived benefits of e-learning systems. It found that students with collective cultural characteristics perceive more individual and organizational impacts than students with individualistic characteristics.

In light of the Covid-19 crisis, [32] carried out a study to assess ISS model constructs' impact on the Malaysia E-learning portal's success based on the comparison between perspectives of male and female students. The results revealed that in both models (female and male), the information quality had a strong effect on user satisfaction and portal usage. In addition, user satisfaction had a significant relationship with E-learning portal success.
Table 1 highlights different studies that utilize the ISS success model to serve the E-learning system context. These studies extend the model, modify its constructs to suit the E-learning context, and propose new dimensions that influence the success of E-learning systems.

Despite the majority of contributions conducted to serve the context of E-learning systems, there is still a lack of works regarding the assessment of E-learning systems adoption during the crisis of COVID-19. Therefore, this study aims to utilize the mentioned extensions and modifications added to the ISS model to build a comprehensive model that assess the extent of the success of E-learning systems adoption in HEIs during the COVID-19 pandemic.

3. Research Methodology

3.1 Research Model

Based on the literature review, different modifications and dimensions have been integrated into the original ISS model. It is critical to consider these extensions when trying to assess the success of E-learning systems. Hence, this study has adopted a model that encompasses significant determinates of the E-learning system success as proven in related studies. This model comprises nine factors that affect each other, whether directly or indirectly, as represented in Figure 3.

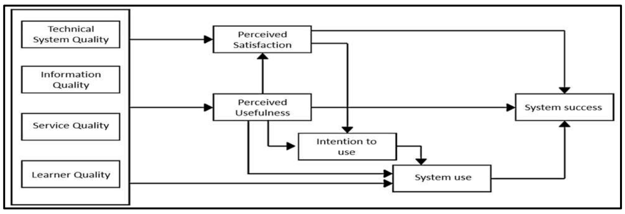

Figure 3: The research framework (adapted from the ISS model)

Table 1: Comparison between some studies that adopted the D&M model in the context of the E-learning systems

Reference	Purpose	Adopted model dimensions	Results
[27]	Assessing the success of an E-learning system called Online Instructor Suite (OIS)	• Information Quality • System Quality • System Usage • User Satisfaction • System Success	There was full support for the effect of quality antecedents on system usage and user satisfaction. It revealed that user satisfaction has a significant effect on OIS success more than the impact explained by system usage.
[28]	Assessing the impact of quality factors on the learners' intention to use the E-learning system.	• Information Quality • Service Quality • System Quality • Instructor Quality • Perceived Usefulness • Perceived Ease of Use • Perceived Enjoyment	It asserted that quality factors (i.e. information quality, service quality, system quality, and instructor quality) are considered critical determinants for user perception towards the E-learning system.
[29]	Determining the critical factors that affect the students' continuance intention to use the e-learning systems in academic libraries.	• Information Quality • System Quality • Service Quality • Perceived Value • User Satisfaction • Intention of using E-learning system	It demonstrated that the quality antecedents have a significant effect on perceived value and user satisfaction, which both in turn affect students' continuance intentions of using e-learning systems.
[26]	Presenting a model for evaluating LMS success implemented in HEI by adopting the updated D&M model, and re-naming its constructs. It evaluated the relationships between the D&M model constructs in the context of LMS.	• Course Quality • System Quality • Service Quality • Learner Satisfaction • LMS Use • Perceived Net Benefits	Student satisfaction is not influenced significantly by the quality of the system and the quality of services. The quality of the course was the exclusive determinant of the satisfaction of the user
[31]	Investigated the role of cultural characteristics of students (individualism and collectivism) on E-learning systems success.	• System Use • User Satisfaction • Individualism/Collectivism • Individual Impact • Organizational Impact	It verified the primary role of the cultural dimension on the perceived benefits of e-learning systems. Hence, it proposed a new dimension for the D&M model called cultural construct (i.e., individualism/collectivism)
[29] [33]	Identifying the main factors responsible for the acceptance of an E-learning system called Canvas LMS by Nigerian students.	• Information Quality • System Quality • Service Quality • Behavioral Intention • User Satisfaction • Actual Usage	It indicates that the information quality and system quality are considered critical determinants for students' behavioral intentions to use the E-learning system. At the same time, student satisfaction is affected only by the quality of services. It also supported the role of both student satisfaction and behavioral intentions on the actual usage of Canvas LMS.
[34]	Examining the success of the E-learning system based on students' perspectives at a public university in Italy.	• Information Quality • System Quality • System Usage • User Satisfaction • System Success	It supported the relationships between dimensions except for the effect of information quality on system usage.
[30]	Investigating the role of user satisfaction in the relationship between perceived value and continuance intention	• Perceived Value • User Satisfaction • Continuance Intention	It confirmed that user satisfaction is an integral part of the association between perceived value and continuance intention to use the E-learning system.
[10]	Determining the factors that affect the E-learning system success by developing a comprehensive E-learning system evaluation model.	• Quality antecedents (i.e. technical system quality, information quality, service quality, educational system quality, support system quality, learner quality, and instructor quality) • Perceived satisfaction • Perceived usefulness • System use Benefits	It revealed that all quality antecedents strongly affect the student's perceived satisfaction. At the same time, five of them are associated with perceived usefulness: technical system quality, information quality, support system quality, learner quality, and instructor quality. Four factors are mentioned as determinants of the E-learning use: educational system quality, support system quality, learner quality, and perceived usefulness. Finally, the E-learning system's ultimate benefits are explained by all three antecedents: perceived usefulness, perceived satisfaction, and system use.
[35]	Investigating the dependency between E-learning service quality attributes, overall E-learning service quality, student satisfaction, and student loyalty.	• E-learning service quality attributes • Overall E-learning service quality • Student satisfaction • Student loyalty	It found that there are three E-learning service quality attributes that have a strong positive impact on the overall e-learning service quality: E-learning system quality, E-learning instructor and course materials quality, and E-learning administrative and support service quality. Also, the overall e-learning service quality strongly related to student satisfaction that ultimately improves the loyalty of students
[32]	Examining the impact of ISS model constructs on the success of the Malaysia E-learning portal during the COVID-19 pandemic based on the comparison between perspectives of male and female students	• Information Quality • System Quality • Service Quality • User Satisfaction • System Use • E-learning Portal Success	The results revealed that the D&M model constructs affect differently among female and male groups. However, in both groups, the information quality had a strong effect on user satisfaction and portal usage, while system quality only affects user satisfaction. Also, user satisfaction had a significant relationship with E-learning portal success.

3.2 Constructs and Hypotheses

The research framework presented in Figure 3 consisted of 9 interdependent factors of E-learning system success. In the following sections, we will discuss each aspect in detail and formulate associated hypotheses:

3.2.1 Technical System Quality

The term System Quality represents different measurement variables, including ease of use, reliability, functionality, flexibility, data quality, portability, integration, and importance [20]. In this research, Technical System Quality is assumed to have implications on three dimensions: Perceived Satisfaction, perceived Usefulness, and System Use. The positive relation of System Quality towards System Use within the E-learning context has been proven by [36] to be a significant positive relation; the relationship between System Quality and User Satisfaction has been investigated by [10, 34] to influence relations positively. While the dimensions of system quality and perceived usefulness are proved to be significantly effective by [37]. The research's collective evidence indicates that System Quality has a direct positive relation towards all three dimensions. Meaning that inflation of Technical System Quality in terms of measurable factors of availability translates into a higher satisfaction perception, usefulness, and higher rate of use. In turn, the following hypotheses are suggested:

- H1.a: Technical System Quality positively impacts the Perceived Satisfaction with the E-learning system during the COVID-19 pandemic.
- H1.b: Technical System Quality positively impacts the Perceived Usefulness of the E-learning system during the COVID-19 pandemic.
- H1.c: Technical System Quality positively impacts the Use of E-learning systems during the COVID-19 pandemic.

3.2.2 Information Quality

Our study's bounds identify Information Quality within the variables of accessibility, usability, understandability, usability, content design quality, up-to-date content, and clarity. The Information Quality dimension [20] research directly affects Use and User Satisfaction. The relations are proven by [33] within the context of E-learning. The third relation investigated is the impact of Information Quality on Perceived Usefulness, conducted by [10], and concluded a positive direct effect between those two factors. Similarly, [38] found the same result within Web-based E-learning systems. This study will investigate the three relations within the domain of E-learning systems adoption during COVID-19 by proposing the following hypotheses:

- H2.a: Information Quality positively impacts the Perceived Satisfaction with the E-learning system during the COVID-19 pandemic.
- H2.b: Information Quality positively impacts the Perceived Usefulness of the E-learning system during the COVID-19 pandemic.
- H2.c: Information Quality positively impacts the Use of E-learning systems during the COVID-19 pandemic.

3.2.3 Service Quality

As identified by [20] an integral role in the model relating to the introduction of Service as a product, the estimate of importance is on par with information quality. This factor tested within several instrument items serving as an indication of the quality level, including tangibility, reliability, responsiveness, assurance, and empathy. Within our study's boundaries, the Service Quality dimension is proposed to directly affect Perceived Satisfaction, Perceived Usefulness, and System Use. The relation between Service Quality and both Satisfaction and use originates from the Original ISS model, further proven alongside the effect on Perceived Usefulness in [10] within the context of E-learning. While [39] adopted an empirical approach in analyzing the different possible dimensions and relations to be applied in the ISS model. The assumed hypotheses for the used model in our study regarding the Service Quality dimension are:

- H3.a: Service Quality positively impacts the Perceived Satisfaction with the E-learning system during the COVID-19.
- H3.b: Service Quality positively impacts the Perceived Usefulness of the E-learning system.
- H3.c: Service Quality positively impacts the Use of E-learning systems.

3.2.4 Learner Quality

The Learner Quality dimension role in measuring E-learning system success has been studied by either focusing on certain definable learner qualities or generalizing an abstract view of the learner. The measurement of learner qualities can identify learner Quality; it can include self-efficacy, attitude, involvement, and the learner's computer anxiety [10] [40] demonstrated the role of the construct by examining the effects of Lerner's self-efficacy on the use. Similarly, [41] concludes that the dimension positively affects acceptance and use. While [8] found that the learner quality dimension as a whole has a highly significant role of impact on perceived satisfaction. A study made by [10] applied an empirical analysis to examine the constructs' effect on perceived usefulness, perceived satisfaction, and use. The results of the previous studies support the following hypotheses:

- H4.a: Learner Quality positively impacts the Perceived Satisfaction with the E-learning system during the COVID-19.
- H4.b: Learner Quality positively impacts the Perceived Usefulness of the E-learning system during the COVID-19.
- H4.c: Learner Quality positively impacts the Use of E-learning systems during the COVID-19.

3.2.5 Perceived Usefulness

Perceived usefulness refers to an individual's willingness to use the information system based on the degree of improving performance the user believes will obtain [19]

The study [10] explained that student perspective on how the E-learning systems enhanced the student learning performance and activities increasing by that student satisfied and affected the E-learning systems use. The authors mention that the perceived usefulness is the key determinant for both students' perceived satisfaction and system use and eventually positively influences students' benefits. The same results were obtained on the positive impact of perceived usefulness on both intentions to use and actual service by [42]. Consequently, in a study conducted by [43] the more significant perceived usefulness of the E-learning system, found to have a substantial effect on E-learning usage intention. Therefore, we assume the following hypothesis:

- H5.a: Perceived Usefulness positively impacts the Perceived Satisfaction of the E-learning system during the COVID-19
- H5.b: Perceived Usefulness positively impacts the System Use of the E-learning system during the COVID-19
- H5.c: Perceived Usefulness positively impacts the Intention to Use of the E-learning system during the COVID-19
- H5.d: Perceived Usefulness positively impacts the E-learning System Success during the COVID-19

3.2.6 Perceived Satisfaction

This construct measures user attitude towards the information system, the user perceptions of their needs, goal, desires are met. An information system refers specifically to the successful interactions between the information system and its users [20]. According to [43, 44], perceived satisfaction significantly affected the user's continuous intention about using the E-learning system; increased perceived satisfaction will increase the Intention to use subsequently increases usage [20]. Previous studies highlighted the strong relationship between perceived satisfaction and net benefits [10, 34, 36, 42]. The user's more perceived satisfaction about the E-learning system leads to an increase the more likely to continue using the system and perceive the E-learning system as beneficial and successful. Based on that, we proposed the following hypotheses:

- H6.a: Perceived Satisfaction positively impacts the Intention to Use of the E-learning system during the COVID-19.
- H6.b: Perceived Satisfaction positively impacts the E-learning System Success during the COVID-19.

3.2.7 System Use

System use is one of the important indicators of the IS success model, which refers to actual usage in the information system measures everything from a visit and navigating the website, information retrieval to the execution of a transaction [20]. In [34] research, they argued that the system's characteristics, such as its accessibility, interactive and user-friendly interface, increased system usage, effectively improve the positive impact on the benefits perceived the E-learning system as a successful system. Another study found a significant effect of the system's use on the benefits [42]. Accordingly, the current study proposes the following hypothesis:

- H7: The System Use positively impacts the E-learning System Success during the COVID-19.

3.2.8 Intention to Use

Intention to use is the likelihood of the user attitude toward information system, before the actual use of the information system and predict the intention to use in future, intention to use is related to the user's attitude, and in the comparison, system use referring to users' behavior [20]. Previous studies [33, 43, 45] have shown that intention to use has a significant relationship with E-learning's actual usage systems. Thus, we hypothesis that:

- H8: Intention to Use positively impacts the System Use of the E-learning system during the COVID-19.

3.2.9 System Success

The original Information System Success model proposed by [20] categorized the Benefits within two dimensions: Individual Impact and Organizational Impact. In contrast, the revisited model combined the two dimensions under Net Benefits. The net benefits represent the overall positive outcome gained by an organization or an individual that belongs to a certain organization, be it in monetary terms or educational terms [20]. A study by [34] refers to the net benefit dimension as the System Success dimension; they explained that the E-learning system's success is likely to increase if the student perceived the system as a beneficial system. The effects from the ISS model on the benefits dimension is what indicates if the E-learning system is successful or not.

3.3 Instrument Development

This study's survey instrument was developed by borrowing items from valid and reliable scales existing in the literature. The items for measuring the quality antecedents' factors, Perceived Usefulness, Perceived satisfaction, System Use, and Benefits, are adapted [10]. The items to measure the Intention to Use factor adapted from [30]. All items used a 5- point Likert scale ranging from (1 = "strongly disagree") to (5 = "strongly agree"). The questionnaire was distributed using two languages: English and Arabic, originally was developed in English and then translated to Arabic. After the instrument was developed, responses of 40 students were gathered to examine the reliability of the survey. The final Cronbach's alpha coefficient value for the total survey is 0.973

3.4 Data Collection and Sample

The data was collected from Saudi students of HEIs using one of the E-learning systems during COVID-19, A recent research about LMS used in HEIs in Saudi Arabia [46] found that 25 out of the 28 public universities in Saudi Arabia implement Blackboard, while two universities use Moodle, and one employs Desire2Learn system. Therefore, this study focuses on investigating the implementation of the three mentioned LMS systems. The online survey is prepared and distributed using the convenience sampling technique, a nonprobability sampling technique used in vast populations where random sampling is impossible. In the conventional process, the sample is ready, and the participates are easily accessible. Therefore, this method is quick and inexpensive [47. 48]

In total, 403 responses were received from the distributed survey, the collected demographic data for the study were analyzed, as in table 2.

Most of the study participants were females more than males by 73% compared to 23%. Further, into the comparison, the undergraduate students were 88.3% out of the study population, and the postgraduates were 11.7%. The replies are received from HEIs students who experience e-learning systems for less than a year or between one and two years or more than two years with percentages of 59.1%, 26.8%, and 14.1%. Moreover, nine different faculties students and others were targeted. Most of the study responses were from computing and information technology and faculty and economics and administration faculty, with 21.3% for both.

4. Analysis and Results

[49] mentioned two distinct generations of statistical techniques responsible for assessing the causal relationships among variables. In the first generation, specifically through the 1980s, factor analysis and regression analysis were dominated and extensively used. However, in the early 1990s, a significant shift occurred toward more sophisticated multivariate analysis methods, referred to as Structural Equation Modeling (SEM). There are two types of SEM, Covariance-Based SEM (CB-SEM) and Composite-Based SEM, also known as Partial Least Squares SEM (PLS-SEM). According to [49], PLS-SEM is more suitable for assessing causal relationships in complex models; therefore, we implemented the PLS-SEM in this research due to our adopted model's complexity that includes nine dimensions and 20 relationships. The PLS model assessment consists of two main steps: first is assessing the measurement model (represented in Section 4.1) and then assessing the structural model (represented in Section 4.2). SmartPLS version 3.0 has been used as a platform to conduct PLS-SEM.

4.1 Measurement model

The measurement model, or named the outer model, describes the relationships between the latent construct and its indicators. There is a need to assess the measurement model to ensure the reliability and validity of its indicators. In this study, the measurement model's reliability and validity have been evaluated using different recommended criteria.

4.1.1 Reliability of Measurement model

- Indicator Reliability: outer loading for each indicator should be ≥ 0.70, but in the case of an indicator with exterior loading between 0.40 and 0.70, we need to examine the impact of deleting or remaining the indicator on the value of Average Variance Extracted (AVE) and Composite Reliability (CR) [49]. It should be considered for excluding the indicator only when removing it leads to an increase in both measures above the suggested threshold. As a result, one item has been deleted from the Technical System Quality construct. The results of indicator reliability for all indicators are displayed in Table 3.
- Internal Consistency Reliability: by using two different measures: Cronbach's alpha (α) and CR. The cut off value is ≥ 0.70 for both measures [50]. As is shown in Table 3, the values of Cronbach's alpha and CR for all constructs are above the minimum requirement.

4.1.2 The validity of the measurement model

To evaluate measurement model validity, two types of validity tests are needed [10, 19]:

a) Convergent validity: refers to the degree to which a measure correlates positively with other measures of the same construct. The main criterion to assess the convergent validity is AVE, which should be ≥ 0.50 [51]. The results of AVE for all constructs were meet the threshold value as represented in Table 3.
b) Discriminant validity: is concerned with assessing how a specific construct indeed differs from other constructs. It has measured by using Fornell-Larcker criterion and cross-loadings 50, 51].

4.1.3 The Fornell-Larcker scale analysis

It is a more traditional approach to assess the validity of constructs by comparing AVE's square root with the correlation results with other constructs [49, 51]. This criterion is based on the logic that a construct shares more variance with its corresponding indicators than with any other construct. The correlation matrix for the Fornell-Larcker method is presented in Table 4. It is clearly shown that diagonal values (square root of the AVE values) for each construct are more significant than the correlation scores with other constructs (nondiagonal values).

Table 2: Demographic Characterization of the Research Sample

Sample characterization		Frequency N= 403	Percentage
Gender	Male	109	27.0%
	Female	294	73.0%
Age	Less than 21	164	40.7%
	From 21 to 30	232	57.6%
	More than 30	7	1.7%
Enrolled Course	Undergraduate	356	88.3%
	Postgraduate	47	11.7%
Experience with the E-learning system	Less than one year	238	59.1%
	1–2 years	108	26.8%
	More than 2 years	57	14.1%
Field of study	Faculty of Medicine	14	3.5%
	Faculty of Economics and Administration	86	21.3%
	Faculty of Art & Humanities	44	10.9%
	Faculty of Computing & Information Technology	86	21.3%
	Faculty of Engineering	40	9.9%
	Faculty of Sciences	28	6.9%
	Faculty of Human Science & Design	22	5.5%
	Faculty of Law	11	2.7%
	Faculty of Commerce	10	2.5%
	Other	62	15.4%
Nature of using the E-learning system	Access learning resources only.	14	3.5%
	Access learning resources and accomplish and submit assignments or quizzes only.	71	17.6%
	Access learning resources, accomplish and submit quizzes, interact with instructors and colleagues	311	77.2%
	Access learning resources, interact with instructors and colleagues	7	1.7%
Type of the E-learning system used	Blackboard	402	99.8%
	Moodle	1	0.2%

4.1.4 Cross-loadings analysis

Cross-loadings analysis indicates the indicators' outer loading on its assigned construct should be greater than any of its cross-loadings (i.e., its correlation) with other constructs [49]. The retrieved cross-loadings results indicated that each indicator has an outer load on its associated construct greater than its cross-loadings with other constructs.

4.2 Structural model

The second step after confirming the suitability of the measurement model is examining the model's predictive capabilities and testing the research hypotheses. In this section, we followed the structural model assessment criteria suggested by [49] and the criterion proposed by [52], to evaluate the overall fit of the model.

4.2.1 Assessment of Collinearity:

It is crucial to verify there are no collinearity problems between the model's constructs before assessing the causal relationships [49]. Covariance Inflation Factor (VIF) is a common measure for detecting collinearity symptoms and according to [49], the VIF value >= 5 indicates potential collinearity issues within the model. All the retrieved VIF values are within the suggested threshold value; hence, there are no collinearity issues between the constructs of the model.

4.2.2 Hypotheses testing - Path Coefficient

The significance of the path coefficient (β values) is evaluated using the bootstrapping technique. This non-parametric re-sampling method randomly draws many subsamples from the original dataset [49]. In this study, we generated 5000 subsamples to assess the significance of paths within the structural model. Retrieved results of the bootstrapping algorithm are represented in Table 5. The p-value indicates the probability of obtaining the t value at least as extreme as the one that is observed [49]. In this study, the accepted threshold of the p-value is 0.05, while the t-value should be larger than the suggested critical value of 1.96 [49]. Thereby, the research hypothesis will accept when the associated t value > 1.96 at a significance level < 5%.

4.2.3 Coefficient of determination (R2):

The coefficient of determination (R^2) is a standard measure used to determine the extent of the variance in endogenous (dependent) variables explained by all exogenous (independent) variables associated with it [49]. In simple words, the R^2 coefficient indicated the combined impact of exogenous variables on the endogenous variable. According to [53] , [53] when the R^2 value is more than 0.67, it is perceived as high, whereas values in the range of 0.33 to 0.67 are within the moderate level, and the R^2 values in the range of 0.19 to 0.33 considered as weak. As seen from figure 4 and table 5, the quality antecedents besides the Perceived Usefulness substantially explain 64.7% of the variance in Perceived Satisfaction with the E-learning system, whereas these constructs explain moderately 62% of the variance in the use of the system. At the same time, the four quality antecedents explain 62% of the variance in the Perceived Usefulness, which is considered moderate. Both constructs, Perceived Usefulness and Perceived Satisfaction, together explain approximately 72% of the variance in students' intention to use the system. Ultimately, a substantial percent (about 70%) of the system success variance is explained by perceived usefulness, perceived satisfaction, and the system's actual use.

4.2.4 *Effect* Size (f^2)

Along with evaluating the R^2 values, there is a need to assess a specific exogenous variable's relative effect on the associated endogenous variable(s), which is given by the effect size f^2 [49]. In this study, retrieved f^2 values have been evaluated by following the guidelines introduced by [54], which indicated f^2 values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects. It is clearly seen from Table 5; there is a large effect from perceived satisfaction and a small impact from perceived usefulness on the endogenous variable 'intention to use'. While perceived usefulness substantially affects perceived satisfaction, it has a small effect on system success and no effect on its actual use. Another small effect noticeable from perceived satisfaction and use of the system on the success of the system. Besides, learner quality moderately affects the perceived usefulness, whereas it has a small effect on system use and perceived satisfaction.

4.2.5 Predictive relevance (Q^2)

Apart from assessing R^2 values as a determinant of predictive accuracy, there is also a need to examine Stone-Geisser's Q^2 value [55], an indicator of the model's predictive relevance or predictive power. According to [49], Q^2 value in the structural model larger than zero for a specific endogenous variable indicated the path model's predictive relevance (i.e., exogenous constructs associated with it). Q^2 values in this study have been calculated by using a Blindfolding procedure embedded in SmartPLS with omission distance (D) equal to 7, as recommended by [49]. Blindfolding is a sample reuse method that systematically omits every dth data point of an endogenous variable's indicators and then estimates the parameters with the remaining data points; to predicts the omitted data points of these indicators. Table 6 shows that the model has a strong predictive relevance where all Q^2 values of all endogenous constructs have considerably exceeded the cut-off value (i.e., larger than zero). More precisely, perceived satisfaction and intention to use have the highest Q^2 values (0.676) and (0.651), respectively, followed by perceived usefulness (0.509), system success (0.464), and, finally, system use with (0.414) value.

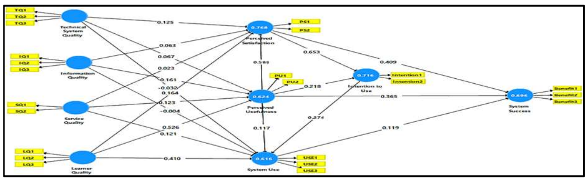

Figure 4: Results of the structural model analysis

4.2.6 Assessment of Model Fit

The last step after determining the model's predictive accuracy and power is to assess the model's fit. The model fit is defined by [49] as " how well a hypothesized model structure fits the empirical data and, thus, helps to identify model misspecifications." To assess the fit of the model, we followed the following recommended criteria:

1. Standardized Root Mean Square Residual (SRMR) is an absolute measure of model fit defined as the square root of the sum of the squared discrepancy between the observed correlation and the predicted correlation [56]. According to [49] there is no agreed threshold value for SRMR that has been introduced in a PLS-SEM context yet. However, [56] suggested that the value ≤ 0.08 appears to be more suitable for the PLS path models. In this study, the SMRS value has been calculated using a consistent PLS (PLSc) algorithm, which provides corrected estimates for the model with keeping all strengths of the standard PLS algorithm [49]. The retrieved SRMR value from PLSc is 0.034, which is considerably less than the suggested cut-off value.
2. Normed Fit Index (NFI) is one of the earliest fit measures introduced by [57] in 1980. NFI is an incremental fit index that assesses fit by comparing the tested model with a restricted null model assumes that all observed variables are uncorrelated. [57] recommend that NFI value should be greater than 0.90 to indicating a good model fit. Like SRMR, we used the PLSc algorithm to calculate the NFI value. As a result, the retrieved NFI value is 0.922, which exceeded the cut-off point.
3. The goodness of fit (GoF) is proposed by [52] as a global model fit measure concentrating on assessing the model's overall prediction performance. It is obtained by calculating the geometric mean of two measurements: AVE and R2 of all endogenous constructs. [58] indicated GoF's value greater than 0.36 is suggestive enough of a good model. Using the following formula [59], GoF's value has been retrieved is 0.73, representing a sufficient overall model validity.

$$\text{GoF}=\sqrt{\overline{AvE} \times \overline{R^2}}$$

Table 3: The fornell-larcker discriminant validity correlation matrix

Constructs	System Success	Information Quality	Intention to Use	Learner Quality	Perceived Usefulness	Perceived Satisfaction	Service Quality	System Use	Technical system Quality
System Success	**0.826**								
Information Quality	0.653	**0.873**							
Intention to Use	0.734	0.658	**0.957**						
Learner Quality	0.682	0.731	0.704	**0.863**					
Perceived Usefulness	0.796	0.679	0.774	0.762	**0.911**				
Perceived Satisfaction	0.804	0.692	0.839	0.762	0.850	**0.945**			
Service Quality	0.577	0.679	0.524	0.575	0.576	0.576	**0.887**		
System Use	0.654	0.613	0.693	0.735	0.687	0.692	0.545	**0.835**	
Technical System Quality	0.642	0.751	0.623	0.721	0.642	0.683	0.614	0.580	**0.832**

Notes: Diagonal values are square roots of average variance extracted (AVE), off-diagonal values are correlations scores.

Table 4: Hypothesis testing results

Hypothesis	Path	β coefficients	T Statistics	P Values	f^2	Decision
H1. a	Technical System Quality -> Perceived Satisfaction	0.125	2.631	0.009	0.024	Supported
H1. b	Technical System Quality -> Perceived Usefulness	0.067	1.126	0.260	0.004	Rejected
H 1.c	Technical System Quality -> System Use	-0.032	0.592	0.554	0.001	Rejected
H 2. a	Information Quality_ -> Perceived Satisfaction	0.063	1.209	0.227	0.005	Rejected
H 2. b	Information Quality_ -> Perceived Usefulness	0.161	2.5	0.012	0.022	Supported
H 2. c	Information Quality_ -> System Use	-0.004	0.068	0.946	0.000	Rejected
H3. a	Service Quality_ -> Perceived Satisfaction	0.023	0.581	0.561	0.001	Rejected
H3. b	Service Quality_ -> Perceived Usefulness	0.123	2.233	0.026	0.021	Supported
H3.c	Service Quality_ -> System Use	0.121	2.441	0.015	0.019	Supported
H4. a	Learner Quality -> Perceived Satisfaction	0.164	2.699	0.007	0.035	Supported
H4. b	Learner Quality -> Perceived Usefulness	0.526	8.801	0.000	0.290	Supported
H4.c	Learner Quality -> System Use	0.41	6.342	0.000	0.131	Supported
H5. a	Perceived Usefulness -> Perceived Satisfaction	0.589	11.477	0.000	0.563	Supported
H5. b	Perceived Usefulness -> System Use	0.117	1.694	0.090	0.010	Rejected
H5.c	Perceived Usefulness -> Intention to use	0.218	3.539	0.000	0.046	Supported
H5. d	Perceived Usefulness -> System Success	0.365	5.648	0.000	0.113	Supported
H6. a	Perceived Satisfaction -> Intention to use	0.653	10.717	0.000	0.417	Supported
H6. b	Perceived Satisfaction -> System Success	0.409	7.09	0.000	0.140	Supported
H7	Intention to use -> System Use	0.274	3.879	0.000	0.069	Supported
H8	System Use -> System Success	0.119	2.629	0.009	0.023	Supported

Table 5: Coefficient of determination (R^2) and Predictive relevance (Q^2)

Constructs	R^2	R^2 Adjusted	Q^2
Intention to use	0.716	0.715	0.651
Perceived Satisfaction	0.768	0.765	0.676
Perceived Usefulness	0.624	0.620	0.509
System Use	0.616	0.610	0.414
System Success	0.696	0.694	0.464

5. Discussion

This research is formulated to examine the use of an extension of the ISS model to measure the execution efficiency of E-learning systems, with closer inspection towards system employment within the duration of the COVID-19 pandemic. The ISS extension model entails the containment of the following dimensions: Technical System Quality, Information Quality, Service Quality, Learner Quality, Perceived Satisfaction, Perceived Usefulness, Use, Intention to Use, and System Success. Each dimension mentioned was hypothesized to play a role in directly or indirectly impacting the level of execution efficiency of the E-leaning system during the global COVID-19 pandemic precaution procedures.

H1.a hypothesized that Technical System Quality positively impacted the Perceived Satisfaction with the E-learning system during the COVID-19 pandemic and was found to match the results produced by [34]. Thus, declaring that the aspects of ease of use, easy to learn, system availability, and reliability and fulfillment are high determents to the Perceived satisfaction made by the system user during the COVID-19 pandemic precaution procedures implementation. The results also support the recent studies of [10]. While H1.a has been proven to match previous studies, H1.b testing unexpectedly produced a negative result in terms of support. This translates to an indication that system users are not heavily or relatively impactful towards the perceived Usefulness held towards the system. The result contradicts the studies of [37] that contributed in the positive impact relation. H1.c hypothesized that the Technical System Quality positively impacts the Use of E-learning systems during the COVID-19 pandemic. The statistical study rejected the hypothesis translating to the indication that Technical System Quality aspects are not necessarily impactful on the system's rate of usage. This could be justified because system usage in the case of E-learning is not necessarily voluntary; the use rate is relatively not up to the student and could be proportionate to the education institution requirement and force to use in the time of the pandemic. The found results contradict that of [36] and [10], where the mentioned studies examine E-learning systems that are not partially forced in usage. H2.a and H2.c did not gain empirical support. Implying that the Information Quality aspects of information sufficiency and conciseness do not necessarily have a high impact on the use and perceived satisfaction, this result matches that of [33, 45], which contradicts the primary assumption of [20]. The result could be affected to match the concern that [20] acclaimed that Information Quality degree of impact on use relates positively to the domain of implementation voluntary use degree. While H2.b hypothesized that Information Quality positively impacts the Perceived Usefulness of the E-learning system during the COVID-19 pandemic, the empirical study supported the high impact relation of Information Quality aspects to the viewed usefulness of the system. The result matched with [38] in search of E-learning web-based system and with [10] for further proof of the high impact relation, meaning that the accurate representation and update of the learning material and system content increases the likelihood of learners to perceive the system to be more useful.

H3.a testing results did not support the assumption that Service Quality positively impacts the Perceived Satisfaction, entailing that providing assistance and guidance throughout system functions and services is not determent informing the user-perceived satisfaction. While H3.b and H3.c were empirically-supported, implying that the existence of proper support service and service communication channels and ease of reaching support services is essential in forming user satisfaction and maximizing intention to use, supported by [10] in similar high impact results. H4.a, H4.b and H4.c were tested to examine the possible impact of leaner quality aspects on the degree to which the learner would use or intend to use the system and how well the system is perceived as inefficiency. The empirical results dominated on the support spectrum in all three hypothesized relations, arguing that the degree of self-efficacy, positive attitude rate and previous experience play an impactful role on to the mentioned dimensions, implying that the measurement of successful implementation can partly rely on the learner quality aspects and not entirely on the actions taken by the HEIs in employing the system. The results are supported by previous studies that proved the empirical weight of learner qualities in measuring the efficiency of e-learning systems [40, 60, 61]. While the hypotheses tested are supported to match the exact empirical test of [10].

H5.a, H5.c, and H5.d gained empirical support, meaning that there is a significant clear impact of perceived usefulness rates onto the intention to use that is generated within the user mindset and perceived satisfaction, alongside a dominant effect onto the benefits harvested by the user from the E-learning system. The empirical result is expected from examining the previous studies of [10, 42]. While the hypotheses H5.b unexpectedly did not gain support and translated to the non-impactful relation of Perceived usefulness aspects, such as agility of accomplishing tasks and effective learning onto actual system use.

Another hypothesis that landed on the support spectrum is H6.a supported by both [43, 44], proving that the user satisfaction with the system is detrimental in inciting an increase in the user intention to use the E-learning system. To add to that, H6.b that hypothesized that Perceived Satisfaction positively impacts the student' Benefits during the COVID-19 pandemic precaution procedure period, found definitive empirical support matching that of [10, 36, 42]. Verifying that increase in perceived satisfaction of the E-learning system leads to an increase in the likelihood of continuing using the system and increasing the E-learning system's perception as beneficial.

H7 hypothesizes that an increase in benefit restored from the system is increased proportionally with the system's actual usage while in the time of precautionary measures taken to deal with the COVID-19 pandemic. As expected, the hypothesis is supported empirically and by literature works that display the dimensions relation within the E-learning system domain [10, 42, 44]. The final hypothesis examined is previously studied and proven to be supported by [33, 45] and has been empirically supported in this research. The learner's Intention to use the E-learning system directly affects the rate at which the actual usage is found.

6. Practical Implications

The practical implications of this research result imply several recommendations and focus points needed to improve directly or in-directly the state of E-learning systems or, as named in this research, “System Success.” While conducting this research, it is highly evident that similar work is needed to mirror the current pandemic regulations with consideration of adapted measurement dimensions.

The statistical results of this study provide higher education institutions with indicators that would help maximize system success; for example, the results proved that the Technical System Quality in terms of how easy to use, degree of flexibility, and reliability have a high direct impact on how a student perceives the usefulness of the system. In short, we can recommend that focusing on designing a system with generally known elements of use, including icons, terms, and colour indications with clear instructions, would be in the best interest of both the Institution and the students.

Results also yield the effect of Information quality of the system onto Perceived usefulness, where can be concluded that the constant review of the information provided by the system, be it course content, course instructions or just simply organization introductory information to be up to date, written clearly and easily understood should be focused on to increase the degree of system perceived usefulness.

Another implication is based on the proven impact relation of service quality onto perceived usefulness and system use. Translating to set the recommendation of focusing on providing guidance services and support technical assistance to increase the overall perceived usefulness and maximize students' voluntary use. Lastly, the recommendation stems from the proven impact of the student’s level of quality in terms of self-efficacy, attitude, and previous experience onto the perceived satisfaction, usefulness, and actual use. Providing that organizations can increase the mentioned impacted dimensions by directing students’ attitude to a more positive view of the system. It can be achieved by studying the demographic, behavioral and psychological segmentation of the students in an ethical way and employing results to the system's design.

The core goal of maximizing system success can be implemented by using this study's results in different ways. As it provides empirical results to an issue that is current to the pandemic regulations and future use for E-learning success as a whole. This study also provides a model that consists of a number of proven dimensions for future studies on the topic.

7. Conclusion

As a response to the COVID-19 outbreak, most educational institutions have enforced E-learning systems as an alternative for traditional education way. The COVID-19 pandemic draws a thick under-line on the importance of embracing a constant measurement of where used E-learning systems lay on the spectrum of implementation efficiency and, in turn, needs to examine possible enhancement points. In this regard, this study has been conducted to assess E-learning adoption success during the COVID-19 pandemic and to explore the main determinants of this matter by using an extension of the D&M IS Success model. The adopted model includes nine dimensions that affect system success as mentioned in the literature, namely: Technical System

Quality, Information Quality, Service Quality, Learner Quality, Perceived Satisfaction, Perceived Usefulness, System Use, Intention to Use, and System Success.

An electronic survey that received 403 responses from Higher education students has been used to verify causal relationships among these dimensions through implementing the PLS-SEM statistical method.

This study's results verified the significant effect of Technical System Quality, Learner Quality, and Perceived Usefulness on the Perceived Satisfaction with the E-learning system. Meanwhile, the Information Quality, Service Quality, and Learner Quality have significantly affected the Perceived Usefulness but not affected by the fourth quality dimension, the Technical System Quality. The results also explain that Service Quality, Learner Quality, and Intention to Use are essential drives for E-learning System Use during the Covid-19 pandemic. In contrast, The System Use is not affected by Technical System Quality, Information Quality, or Perceived Usefulness. Along with these results, the Intention to Use the system is significantly influenced by both Perceived Satisfaction and Perceived Usefulness dimensions. Further, the study demonstrates that Perceived Satisfaction, Perceived Usefulness, and System Use are interdependent, and all three have a significant positive impact on E-learning System Success.

This study holds multifaceted contributions, including important implications that educational institutions need to consider to maximize the benefits retrieved from the investment in E-learning systems. Each confirmed relationship indicates the possible improvement through positively enhancing the aspects relating to the determined affecting dimensions. Besides, the study model consists of several proven factors for future studies concerned with E-learning systems' success, especially in crisis times. Consequently, this model confirms the validity of the D&M information systems success model for evaluating the success of E-learning systems during crises and its' viability to be extended to be used in the context of the HEIs

8. Limitations and Future Work

Although the study sample used in this research is selected by fair randomization, it is found in the demographic segmentation of the survey results that 88.3% of the sample population belong to the undergraduate category, which can play a factor since the learner quality is factored in within the empirical study. For future work, an equal segmentation random sampling could be proposed to represent the population better. It is good to mention that the different factors of the population demographic can be manipulated in targeting to produce more focused segments.

A second point can be raised for future work, that the psychological and behavioral factors should be added to the study, reasoning back to that the system success is measured heavily on perception dimensions, to add to that the untraditional circumstances of the pandemic could be adding a negative view into the overall population.

Finally, the DeLone and McLean information systems success model is designed to include the Use dimension as voluntary use. This study factors in the intention to use. In reality, the regulations forced a portion of the service, meaning that it is not a 100% voluntary usage. That could also be weighed and segmented to actual use and voluntary usage in the future.

This research represents the system study within the timeline of the COVID-19 pandemic and could be used for future work within the same concept of forced regulations.

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