Determining the Critical Success Factors (CSFs) Influencing E-learning in High Education, using the Partial Least Squares Structural Equation Modelling

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Abstract

The educational process has been hindered worldwide due to Covide-19 to some extent. Yet, the Egyptian government transitioned to E-learning to maintain the designed educational agenda. Consequently, recognizing the benefits of E-learning and its influence on individuals and society is imperative to link E-learning system with its success drivers. Therefore, the aim of this paper is detecting the main critical success factors that can greatly enhance E-learning in Egypt. The study employed DeLone and McLean model (2003) as a basis for identifying aspects of E-learning success measured by net benefits. Consequently, technological factors, E-learning quality, user attitude, intention to use and user satisfaction are utilized to explain E-learning success. Prior studies ignored the different stakeholders' perspectives about E-learning in Egypt. Sequentially, the study's main contributions are constructing a comprehensive framework that includes two different models; instructors and learners. Furthermore, this paper uses net benefits as an unobserved variable to reflect the E-learning success, using the partial least square structural equation modeling method. Moreover, $\mathrm{PLS}_{\mathrm{predict}}$ is applied to measure models' out-of-sample predictive power. In spite of the $\mathrm{PLS}_{\mathrm{predict}}$ importance, few papers utilized it in the E-learning literature.

The data were collected through online questionnaires and directed to the two stakeholder groups of tertiary education. The results indicate that the two models are empirically and statistically supported, and they adequately demonstrate and predict the interdependency and importance of the selected constructs. Besides, the results of the mediation analysis indicate that for instructors, satisfaction has the highest total effect on net benefits with its direct effect and indirect effect via user attitude and intention to use. For learners, E-learning quality has the highest mediation effect through its indirect effect via satisfaction, attitude and intention to use.

Keywords: DeLone and McLean (D&M) model, E-Learning Success, Egypt, Mediation Analysis, Partial Least Square (PLS).

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1. Introduction

The Sustainable Development Goals (SDGs) set by the United Nations for 2030 had selected higher education as one of the main drivers for global development through "ensuring inclusive and equitable quality education and promoting lifelong learning opportunities for all" (Owens, 2017, p.414). To emphasize, Education for Sustainable Development (ESD) plays an important role in many areas of SDGs, such as: poverty, gender equality, and economic growth.

Unfortunately, the outbreak of the COVID-19 pandemic in 2019 has hindered the educational process to some extent. Yet, the Egyptian government has planned to continue the educational process through shifting from traditional learning to E-learning, to maintain the designed educational agenda. As a result, educational institutions have adopted the E-learning system rapidly. This change had created many challenges for all stakeholders including learners and instructors, therefore universities started to provide training for the academic staff and students to use technology in teaching and learning through different platforms (Muhammad et al., 2020). However, E-learning was not established originally due to COVID-19, it was employed in many Egyptian educational institutions years before the pandemic.

E-learning can be defined as the process of providing 80% or more of the course's content online using the latest Information and Communication Technologies (ICT) (Nagy, 2005; Allen and Seaman, 2014). In fact, E-learning system provides many benefits such as: saving costs and time, encouraging self-learning process, increasing learning accessibility and flexibility, improving stakeholders' performance and providing a variety of methods for students' evaluation (Nagy, 2005). Yet, it still suffers from some limitations, such as encouraging students' indolence, hence reducing effectiveness, lack of communication among students and instructors or with their peers, platforms usage illiteracy, and increasing costs of system's maintenance (Batdı et al., 2021). On the other side, blended learning, in which a proportion of course's content is presented online and the remaining part is presented in traditional learning, may provide a suitable solution for the previously mentioned drawbacks (Allen and Seaman, 2014).

2. Aim of The Study

Despite the rapid adoption of E-learning system, one of the main issues facing officials is reinforcing its success. therefore, the aim of this paper is to determine the main Critical Success Factors (CSFs) which influence E-learning in Egypt. As far as the authors know, among the limitations of the previous studies is disregarding the different stakeholders' perspectives. Thereupon, one of the main contributions of this study is constructing a comprehensive framework that includes two different models one for instructors and the other for learners. Based on the literature, these models were set upon DeLone and McLean (D&M) success model, the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

In addition, this research uses Net Benefits (NB) as an unobserved variable to measure E-learning success and it is examined by means of the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. Furthermore, many PLS path models include mediation effects, yet they are usually not explicitly tested. This paper will test mediation effects and depend on its analysis in providing more rigorous recommendations to improve net benefits received by the two stakeholders through estimating the impact of different constructs on improving E-learning success in Egypt. In addition, PLS_{predict} is applied to measure models' out-of-sample predictive power.

The paper is structured as follows; first, the relevant literature as well as papers related to Egypt are presented. Then research variables, hypotheses and methodology are introduced, followed by the data description as well as the clarification of the descriptive statistics and scoring for both instructors and learners. After that, the results of the two models are specified and illustrated. Finally, the discussion and conclusion are stated as well as recommendations are suggested.

3. Literature Review

Past researches highlighted the importance of determining the CSFs that influence E-learning adaptation and resulting net benefits (Sun et al., 2008; Boateng et al., 2016). Consequently, some studies have investigated the possible CSFs that may affect them. They have argued that this approach could be used by governments to form agendas for further improvements of E-learning systems. Leidecker and Bruno (1984) defined CSFs as constructs, characteristics or circumstances that would have a significant influence on the success of a project.

The information success model presented by DeLone and McLean (2003) is a predominant dimensional model for evaluating the "success" of an operational Information System (IS). According to its most updated version of 2003, several dimensions included to evaluate the E-learning success. These dimensions are system quality, service quality, information quality, intention to use, satisfaction and net benefits. Intention to use, service quality and net benefits are considered newly added dimensions to the model. Service quality in prior studies used to be part of system quality, but recently it becomes an independent component (Wang and Liao, 2008; Hassanzadeh et al., 2012). Moreover, "intention to use" is suggested to be a useful and valuable alternative measure to actual "use" – as a multidimensional concept- due to difficulties in explaining if "use" is effective or ineffective, voluntary or obligatory, informed or uninformed, and so on, as "use" is a behavior, while "Intention to use" is an attitude. Net benefits are considered a comprehensive measure which includes interorganizational, consumer, work group and societal impacts according to Clemons et al. (1993), Brynjolfsson (1996), Myers et al. (1997), and Seddon (1997) respectively.

Reviewing the previous studies about the Egyptian education system, it was detected that the system suffers from many challenges, such as overcrowded classes, transportation issues, lack of resources, in addition to lack of practical work and innovation in programs and courses (El Gamal & Abd El Aziz, 2011; El-Gamal, 2014). Therefore, Egypt has an urgent need to implement E-learning to mitigate and eliminate the conventional education problems. Following, the literature about E- learning implementation and the most important CSFs in Egypt using different methodologies is presented as it is an important issue to develop E-learning.

Utilizing Confirmatory Factor Analysis Structural Equation Modelling (CFA-SEM) approach, Headar et al. (2013) and Abbas et al. (2016) identified technological factors, E-service quality, perceived usefulness, perceived ease of use, intention to use and satisfaction as the key CSFs of E-learning in Egypt, ascendingly. Likewise, a multivariant case-study approach was applied by Abdel-Gawad and Woollard (2015), and they concluded that the most important CSFs in Egypt are: the course content's nature, learners' characteristics, instructors' characteristics and technological factors. Abdel-Wahab (2008) employed the step-wise regression and deduced that the chief factors affecting users' intention to use the system in Egypt are: attitude, perceived usefulness, perceived ease of use, organizational support as well as the cost savings.

In 2011, Eraqi et al. conducted descriptive analysis and stated that E-learner factors, E-instructor factors, IT factors, university factors and E-learning quality are the most important CSFs of the E-learning system. E-learner factors are measured in terms of self-motivation, IT skill, time management and self-discipline, while E-instructor factors are measured by IT competency, teaching style, attitude and mindset. IT factors are represented by infrastructure richness, reliability and capability. In addition, university support for adequate infrastructure is the main measure of university factors. Finally, E-learning quality dimensions encompassed content, technology and services. Using the same technique, others deduced that many users accepted E-learning as an effective instrument for education. However, large number of learners are found to believe that it is challenging to interact either with their fellows or instructors, especially as most of the users suffer from poor computer skills. Consequently, they recommended that blended learning should be implemented to provide the most efficient level of learning and get over the lack of resources and skills (Abdelaziz et al., 2011; Khedr, 2012; El-Seoud et al., 2013; Ghenghesh et al., 2018).

Upon examining the literature rigorously, this study contributes to the literature in many ways whether theoretical or methodological. Regarding the theoretical horizon, many researches did not address the different stakeholders' perspectives; thus, one of the main contributions of this study is carrying out two multi-dimensional comprehensive models; instructors and learners, therefore considering the two perspectives simultaneously for more understanding to the whole picture.

For the methodological side, as far as the authors know, this research adopts the PLS-SEM technique to investigate E-learning success. Furthermore, the mediation analysis is conducted to assist officials in setting better priorities efficiently through identifying the construct, which has the highest importance for the net benefits. Additionally, the paper utilizes $\mathrm{PLS}_{\mathrm{predict}}$ to evaluate the model's out-of-sample predictive power. Despite the importance of the mediation analysis and $\mathrm{PLS}_{\mathrm{predict}}$, few papers utilized them in the E-learning literature (Hair et al., 2016; Sarstedt et al., 2021).

4. Methodology

The constructs, hypotheses of the models as well as the techniques used to analyze them are illustrated.

4.1. Research Variables and Hypotheses

Since E-learning systems are specific type of IS (Hassanzadeh et al., 2012), this paper uses net benefits as a measure for the E-learning success inspired by the updated model of DeLone and Mclean (2003). In addition, upon reviewing the relevant literature, the following constructs are selected as potential CSFs of E-learning system in Egypt. These constructs are Technological Factors (TF), E-learning quality (QU), User Attitude (UA), Intention to Use (IU) and User Satisfaction (US).

This research concerns with two stakeholders namely; students and instructors because they are the core of the educational process and the most affected parties from E-learning. As a promising gauge for the success of E-learning, net benefits are the most suitable, comprehensive and important. It explains the E-learning system influence and captures the balance of its good and bad effects on students, instructors, and even societies (DeLone and McLean, 2003; Hassanzadeh et al., 2012). Consequently, in this study, net benefits are represented by improving users' performance, cost and time savings (Parker and Martin, 2010), as well as societal benefits; less polluted environment and smooth flow of traffic (Campbell and Campbell, 2011).

4.1.1. Technological Factors

Technological factors could be defined as user's belief of having the required skills to use the E-learning system successfully and to which level the country's infrastructure supports the E-learning usage (Conrad and Munro, 2008). Country's infrastructure could be reflected by its ability to provide a reliable internet connection, platforms which support the E-learning process, equipment accessibility and organizations that provide training for the users (Arbaugh and Duray, 2002). According to Bhuasiri et al. (2012), technological factors is one of the CSFs in both developed and developing countries which influences E-learning effectively.

Several dimensions were taken into consideration to quantify technological factors. These dimensions are internet-reliability, technological-quality and medium richness (Volery and Lord, 2000). Based on Daft and Lengel (1986) medium or media richness theory refers to evaluating the communication media based on its ability to support various types of instructional elements (text, audio, pictures and video messages) and to which extent it provides in-time interaction.

In 2015, Tarus et al. discovered that network connectivity, devices and bandwidth of internet are essential to ease E-learning accessibility. In addition, Makokha and Mutisya (2016) claimed that shortage of devices and inadequate internet would affect the E-learning system negatively.

To sum up, developing countries should pay special attention to technological factors in evaluating the E-learning quality, due to their technological challenges compared to developed countries, ensuring the ease of access to the E-learning system and its successful implementation (Al-Azawei et al., 2016). Therefore, it's proposed that:

H_1: Technological factors has a direct positive effect on E-learning quality.

4.1.2. E-learning Quality

Based on the updated D&M model (2003), quality construct can be measured in terms of three different quality types which are system quality, service quality and information quality. According to the previous E-learning literature, the three kinds play a key role in determining users' behaviors for both learners and instructors (DeLone and McLean, 2003). However, for learners' model, the instructor quality should be added as another important indicator of service quality (Lwoga, 2014; Poelmans and Wessa, 2015). Each of the three quality types with its own definition and dimensions will be discussed, as well as the proposed hypotheses of the E-learning quality construct.

4.1.2.1. System Quality

System quality is a multi-dimensional concept representing the hardware and software qualities available to the end-users to fulfill their needs from information (Poelmans and Wessa, 2015). It refers to the quality of the performance of the IS used in the E-learning process (Petter and McLean, 2009); as the system quality characteristics affect the ability of users to operate the system effectively and efficiently (Hassanzadeh et al., 2012).

DeLone and McLean (2003) used system functionality, system availability, response time and ease of use as dimensions for system quality. System functionality refers to the flexible access to the course material provided by the system. Availability refers to the system being available in terms of time and place. In addition, response time should be fast, consistent, stable and secured (Pituch and Lee, 2006). Finally, ease of use refers to the idea that the system is not complex and could be used easily by the users.

4.1.2.2. Service Quality

Service quality is the overall quality of the service and support provided to the users by the service provider either training unit, IT staff or even by instructors (Petter and McLean, 2009; Hassanzadeh et al., 2012). It can be measured through various dimensions as DeLone and McLean (2004) represented service quality by system effectiveness, responsiveness and the existence of technical support. Parasuraman and Grewal (2000) first measured service quality by eleven dimensions, then they merged them to include four dimensions only; service reliability, responsiveness, assurance, and tangibles. Service reliability indicates how the service providers perform the service in an accurate manner, service responsiveness refers to providers' willingness to help the users. Lastly, assurance is the providers' knowledge towards the service, and tangibles refer to providing materials which facilitate the service.

4.1.2.3. Information Quality

Information quality represents the quality of information or the course content that is introduced by the provider and delivered by the system. In addition, it refers to the improvements of the users' performance through using the system (Bhuasiri et al., 2012). That's why information quality could be assessed by learners using the system to determine if the instructor is able to introduce beneficial content that fulfills the learners' needs (Adeyinka and Mutula, 2010).

Prior studies indicate that information quality from learners' perspectives is measured by course content quality (Lee et al., 2009) and course design quality (Liu et al., 2010). Course content quality refers to the quality of the updated course material, while course design quality refers to providing learners with courses which fit their needs. Meanwhile, from instructors' perspective, information quality is measured in terms of effective presentation, ease of designing course and the availability of various evaluation methods on the system (Yengin et al., 2011).

In conclusion, previous studies indicate that, if users believe that the available information on the system is accurate and meets their needs, and the system's performance is stable, consistent and reliable, with organizations providing them with customized support as trained coordinators, technical service engineers, they will recognize the E-learning system as a useful, and easy-to-use system. Consequently, this will affect users' attitudes and satisfaction with the system positively, as well as motivating them to use it again (DeLone and McLean, 2003; Ramayah and Lee, 2012; Xu et al., 2013; Abbas et al., 2016). Based on the above discussion, the following hypotheses will be empirically tested:

H_{2A}: E-learning quality has a direct positive effect on users' satisfaction.

H_{2B}: E-learning quality has a direct positive effect on users' attitude.

H_{2C}: E-learning quality has a direct positive effect on intention to use.

4.1.3. Attitude

Users' attitude represents the users' positive or negative psychological state to perform a certain behavior, as using the E-learning system (Abdel-Wahab, 2008). It can be expressed in terms of the TAM which was firstly introduced by Davis in 1985. TAM is used to indicate the extent to which a favorable users' attitude would affect the acceptance of a new technology (Surendran, 2012). That's why having a positive attitude towards a certain technology as the E-learning system would enhance the probability of accepting it.

TAM, which is based on the TRA (Fishbein and Ajzen, 1977), indicates that users' attitude and surrounding subjective norms lead to behavioral intention, which in turn will result in individual's actual behavior. Using the TRA, Davis (1985) had established two concepts; the Perceived Utility (PU) which could be defined as the promotion of users' performance when using the computer and Perceived Ease of Use (PEOU) which refers to how using the computer is effortless for the users. Bertea (2009) stated that two models were conducted by Rosenberg and Fishbein to measure users' attitude. This paper is based on the Rosenberg model which reflects users' attitude by their perceived utility from the system usage and how using it is important for them.

Alhomod and Shafi (2013) had shown that positive users' attitude is an important factor for determining the E-leaning success. If the users find the system is secured, meets their needs and improves their performance, the users' level of satisfaction will improve and their attitude towards the system will be stimulated directly. Consequently, having a positive attitude will directly affect the users' behavioral intention towards using the system (Liaw et al., 2007). Therefore, the following hypothesis is examined:

H_3: Users' attitude has a direct positive effect on intention to use.

4.1.4. Intention to Use

Intention to use is the possibility to utilize the E-learning system in the future, before indeed using it (Petter and McLean, 2009; Poelmans and Wessa, 2015). It is also referred to as the idea of reusing the system. According to the UTAUT, intention to use is considered a key determinant for the users' acceptance of technology (Lwoga and Komba, 2015). Park (2009) utilized the TAM to examine learners' intention to use the E-learning system with many dimensions, such as learners' attitude, perceived usefulness, perceived ease of use and E-learning efficiency. Further, Lin and Lu (2000) claimed that the main dimensions to measure intention to use are attitude, perceived usefulness and perceived ease of use.

Al-Busaidi and Al-Shihi (2012) indicate that if stakeholders are satisfied with the system usage, this will stimulate them to reuse the system, hence they will receive many benefits such as improving their skills.

Therefore, having the intention to use the system would directly affect the net benefits (DeLone and Mclean, 2003). Accordingly, the paper is going to test the following hypothesis.

H_4: Intention to use has a direct positive effect on net benefits.

4.1.5. User Satisfaction

User satisfaction may be defined as users' overall feeling of fulfillment of their expectations from the system (Sun et al., 2008). At first, it measures the interaction between users and the system and then evaluates the extent to which the outcome of this interaction fits the users' expectations.

Users' satisfaction concept may differ according to different stakeholders' perspective. Regarding learners' perspectives, Arbaugh (2000) identified four dimensions affecting the learners' satisfaction, which are; platform flexibility, usability, perceived usefulness and interactive environment between users. Besides, Bolliger and Wasilik (2009) determined three dimensions influencing instructors' satisfaction; student-related, instructor-related and institution-related dimensions. The student-related dimension is claimed to affect the instructor's perceptions about E-learning net benefits, while instructor-related dimension represents their interest in using technology and the opportunity to teach in a creative way. Finally, the institution-related dimension refers to the support and policies provided by the institution to the instructor. Therefore, if institutions do not provide enough support for the instructor, their satisfaction would be affected negatively as most of instructors believe that online teaching is much more time consuming than traditional face to face teaching (Seaman, 2009).

According to prior studies, if users are provided training, support and encouragement, their satisfaction will be positively influenced. Furthermore, if the users are satisfied with the E-learning system, they will have a positive attitude towards it and their intention to continue using the system will increase. Further, being satisfied will provide the users with a high level of net benefits leading directly to the E-learning success (Urbach et al., 2010). Therefore, the following hypotheses are examined empirically:

H_{5A}: Users' satisfaction has a direct positive effect on intention to use.

H_{5B}: Users' satisfaction has a direct positive effect on users' attitude.

H_{5C}: Users' satisfaction has a direct positive effect on net benefit.

4.2. Partial Least Square Model

The Structural Equation Modelling (SEM) is a vital tool of multivariate statistical analysis for testing hypotheses to analyze the structural theory of a given phenomenon (Hair et al., 2016). These theories present the causal relationships among variables. The SEM allows researchers to include unobservable variables (construct or latent) along with the observed variables (indicators). Although SEM has various types, PLS has been chosen to examine the cause-effect relationship models.

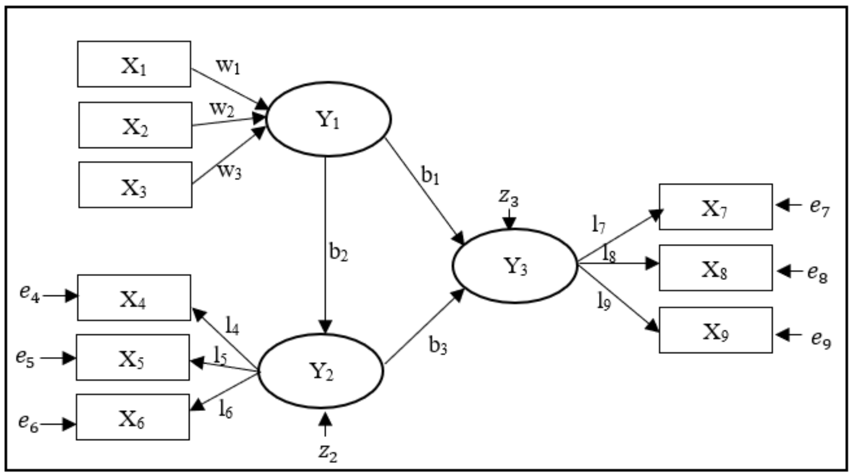
Among the main advantages of the PLS-SEM is that it can accomplish high level of statistical power for small sample size, in addition, it can use non-normal data (Hair et al., 2016). Besides, it handles reflective and formative measured constructs, where it can include large number of indicators in each construct and deal with complex models which include large number of relations.

4.2.1. PLS-SEM Algorithm

PLS-SEM is a variance-based algorithm which is used to measure the magnitude and direction of inner and outer relations by attempting to minimize the unexplained variance and maximize the explained one of regressors. PLS-SEM path model is illustrated in Figure 1.

Figure 1

PLS-SEM Path Model



Source: Sarstedt et al. (2021).

The X_i variables are the indicators which represent the raw data that is obtained from individuals' responses to the questionnaire. These indicators are used as inputs to estimate the constructs. The Y_i variables are known as the constructs.

PLS-SEM is composed of two models, the first is the measurement model which expresses the relationship between the constructs Y_i and its associated indicators X_i i.e. X_1, X_2 and X_3 are the indicators of Y_1. The second is the structural model which explains the relationship between the constructs themselves i.e. Y_1 and Y_2 are used to explain Y_3 as follows.

First: PLS measurement (outer) model can be classified into reflective and formative, where the reflective model shown in Equation 1 reflects a direct relationship from construct to indicators, with a single headed arrow called the loading (l). This loading is estimated by a single regression of each indicator on its corresponding construct (Hair et al., 2016). Indicators are likely to have an error term, as they have a high degree of interdependency which makes them interchangeable.

$$X = lY + e \dots\dots\dots (1)$$

where X is the indicator, Y is the construct, l represents the loading which shows the strength of the relationship between X and Y and e is the measurement error term.

Regarding the formative model shown in Equation 2, it depicts the relationship from the indicators to the construct with a single headed arrow called the outer weight (w). This outer weight is estimated by partial multiple regression, where the construct is the dependent variable and the indicators are the independent variables. PLS-SEM deals with indicators of formatively measured constructs as composite indicators, hence, the construct is free from error (Diamantopoulos, 2011).

$$Y = \sum_{i=1}^{M} w_i . X_i \ldots\ldots\ldots \quad (2)$$

where Y is a linear combination of indicators $X_i (i = 1,2,..M)$, and w_i is the indicator's weight.

Second: PLS structural (inner) model shows the inner relationships between the constructs considering the strength of these relationship by path coefficient (b_1, b_2 and b_3) which resulted from a partial regression of a certain construct as a dependent latent variable i.e. Y_3 on its predecessor independent constructs i.e. Y_1 and Y_2 in Figure 1.

Then it's concluded that the PLS algorithm uses mainly a separate Ordinary Least Square regression (OLS) relationships, which produce the outer weights, loading, path coefficients, indirect effects, total effects and R^2 values (Hair et al., 2016; Sarstedt et al., 2021).

4.2.2. Model Evaluation

Model evaluation can be divided into two steps. Measurement model evaluation is performed to evaluate the reflective and formative models as a first step, then structural model is evaluated next (Hair et al., 2016).

4.2.2.1. Assessment of Measurement Model

Regarding the reflective model, the first assessment aspect is measuring the model's reliability, which shows the stability and compatibility of the measurements. To assess indicator's reliability, the standardized indicator's outer loading should be greater than or equal 0.708 for the indicator to be reliable. If the outer loading's value for a specific indicator is between 0.40 and 0.708, researchers should consider the impact of removing this indicator from the model. However, if its value is less than 0.40, it should be removed. As for constructs' reliability, it can be measured by Cronbach's alpha as in Equation 3 (Sarstedt et al., 2021).

$$Cronbach's\ Alpha\ (\boldsymbol{\alpha}) = \frac{i\bar{r}}{(1+(i-1).\bar{r})} \ldots\ldots\ldots \quad (3)$$

where $\bar{r}$ is the average of the lower or upper triangular correlation matrix, i is the construct's number of indicators.

As indicated by some authors, Cronbach's alpha underestimates the internal reliability (Hair et al., 2016). Alternatively, Composite Reliability (CR) test is applied to examine the reliability of the model by considering the outer loading of indicators as illustrated in Equation 4.

$$\rho_c = \frac{\left(\sum_{i=1}^{M} l_i\right)^2}{\left(\sum_{i=1}^{M} l_i\right)^2 + \sum_{i=1}^{M} \mathrm{var}(e_i)} \ldots\ldots\ldots \quad (4)$$

where l_i refers to the standardized loading of indicator i of a certain construct estimated, using M indicators, e_i is the indicator's error and $var\ (e_i\ )$ is the measurement estimated error variance.

ρ_c values should range from 0 to 1 as the higher the value of ρ_c, the higher the reliability is. If ρ_c value is less than 0.60, there is no consistent reliability. If its value is between 0.60 to 0.70, it is acceptable; between 0.70 and 0.90, it is satisfactory; and finally, values higher than 0.90, it is problematic as they suggest that the indicators are almost the same (Hair et al., 2016).

The second assessment aspect is measuring the model's validity, which explains the degree in which an instrument measures what it is supposed to measure. It is classified into convergent and discriminant validity. Convergent validity exists when indicators of a certain construct share a high proportion of variance. Convergent validity is evaluated by Average Variance Extracted (AVE), as shown in Equation 5. AVE should be greater than or equal 0.50 to indicate that 50% or more of the indictors' variance is expressed by the construct (Sarstedt et al., 2021; Hair et al., 2016).

$$\text{AVE} = \frac{(\sum_{i=1}^{M} l_i^2)}{M} \ldots\ldots\ldots \quad (5)$$

Regarding the discriminant validity, it means that each construct captures different phenomena from other constructs. It is measured by the cross loading and Fornell-Larcker Criterion. The cross-loading states that the outer loading of an indicator of specific construct should be higher than all its cross loading with other constructs. on the other hand, Fornell-Larcker criterion compares the amount of variance captured by the construct (AVE) with the shared variance of other constructs $ø_{ij}^2$. Therefore, the discriminant validity is established only if the AVE is greater than $ø_{ij}^2$, such result implies that the two constructs are sufficiently different in terms of their empirical standards. In 2015, Dijkstra and Henseler presented Heterotrait-Monotrait (HTMT) ratio as a measurement for discriminant validity, where HTMT is the average of all correlations of indicators in every construct relative to the mean of correlations of indicators in the same construct. It is used to estimate the true correlation between any two constructs. Moreover, if HTMT value is lower than 0.90, it indicates that the discriminant validity is established (Sarstedt et al., 2021; Hair et al., 2016).

As far as the formative model is concerned, three different evaluation tests should be applied. First, assessing the convergent validity, it refers to the extent to which a formative indicator contributes to the actual meaning of the formative construct. It can be evaluated by redundancy analysis, where the information of model is redundant in the formative and reflective construct (Hair et al., 2016). Redundancy analysis declares that the path coefficient joining the formative constructs with the reflective of the same construct must be at least 0.70. That's why the researchers must include a reflective indicator through taking an appropriate reflective measure from previous studies or setting a global item. Global item summarizes the core of the formative construct (Hair et al., 2016).

Second is the collinearity problem, which can be evaluated by Variance Inflation Factor (VIF), as represented by Equation 6. If the VIF value is above 5, a higher level of collinearity among indicators exists.

$$VIF_i = \frac{1}{1-R_i^2} \ldots\ldots\ldots \quad (6)$$

where R_i^2 is the R^2value of i-th regressions of i-th indicators.

The third test is to examine the statistical significance and relevance of the indicator weights. This can be done by running a bootstrapping method, which takes a random sub-sample from the main dataset, then estimates the model for each sub-sample and computes the p-values and confidence intervals to determine the significance of the indicators and constructs. Subsequently, if indicator's outer weight appears to be insignificant, the following rules of thumb apply: if the indicator's outer loading is 0.50 or higher, the indicator is still retained. However, if loading is below 0.50 or insignificant, the researchers should strongly consider removing the indicators. Notably, the resulting weights range between +1 and -1 indicating positive or negative relationship among indicators and construct (Sarstedt et al., 2021).

4.2.2.2. Assessment of Structural Model

To assess the structural model, collinearity is measured first using the VIF. Then using bootstrapping, the significance of path coefficients is checked (Hair et al., 2016). Moreover, the path coefficients' values extent from +1 to -1, or from perfect positive to perfect negative relationships between constructs (Sarstedt et al., 2021).

Regarding the in-sample predictive power, the coefficient of determination (R^2) is used to show how much the variance of dependent variable is explained by all the constructs jointly. R^2 values always range from 0 to 1, where 1 represents perfect predictive accuracy (Hair et al., 2016).

Finally, to assess the out-of-sample Predictive power, researchers can utilize $\text{PL}S_{\text{predict}}$. According to Shmueli et al. (2019), researchers should undertake two steps to deploy $\text{PLS}_{\text{predict}}$. First, the $Q^2_{predict}$ of the key target construct of the study and its indicators is assessed where their $Q^2_{predict}$ should be greater than zero to indicate that the PLS path model has predictive power or that it outperforms the Linear Regression Model benchmark. Second, Sarstedt et al. (2021) stated that the degree of prediction error should be evaluated using Mean Absolute Error (MAE) only if the distribution of the prediction error is highly asymmetric, otherwise the Root Mean Squared Error (RMSE) is utilized. Consequently, researchers should check if the PLS-SEM analysis yields lower prediction errors in terms of RMSE or MAE for all indicators, compared to the linear model benchmark. Accordingly, the model has high predictive power if all indicators have lower prediction errors, whereas it has medium predictive power if the majority of indicators have lower prediction errors. On the other hand, the model has low predictive power if the minority of indicators have lower prediction errors, while lacks of predictive power in the model exists if none of the indicators have lower prediction errors.

4.2.3. Mediation Analysis

A mediating effect is formed when variables intervene between two related constructs, creating direct and indirect effects (Hair et al., 2016). To clarify, in Figure 1, direct effects are reflected by the path coefficients linking two constructs, for example b_1 between Y_1 and Y_3, while indirect effects are the relationships that encompass a sequence of path coefficients with at least one intervening construct i.e. b_2 then b_3 connecting Y_1 and Y_3 via Y_2. Hence, this indirect effect is characterized as the mediating effect and Y_2 is characterized as the mediator.

The main idea of the mediation analysis is to explain the causality between the constructs i.e. higher quality of an IS is positively correlated with its acceptance and success, but it does not signify the existence or absence of a direct causal relationship between them. Consequently, the mediation analysis is used in this study to evaluate and measure accurately the real causal-effect relationships between constructs, as the empirical results may differ from results based upon prior theories. The mediation effect is divided into two types; partial mediation, which means that the direct and indirect effects are significant statistically and theoretically, and complete mediation, which means that only the indirect effect is significant. In order to determine the statistical significance of each effect, bootstrapping technique is utilized. Subsequently, the analysis would depend on the total effect of a construct on the key target construct which is measured by adding the significant total direct and indirect effects of each construct. Consequently, the total effects of the constructs depict the amount by which the improvement in each construct will enhance the E-learning success.

5. Data

Data were collected through anonymous online questionnaires administrated to two stakeholder groups at higher education institutions in Alexandria, Egypt during the second semester of 2021, namely; instructors and learners. The questionnaires contained different types of questions as Likert scale, multiple response and open-ended questions, consequently, respondents can express their opinions. The five-point Likert scale questions ranges from 1 to 5, where 1 is assigned to strongly disagree and 5 to strongly agree. These questionnaires are statistically analyzed by SmartPLS 3 software (V. 3.3.3).

The first part of the questionnaire targets respondents' demographic characteristics. A total of 100 valid and complete instructors' responses were collected, including 33% male respondents and 67% females, while 320 students have responded including 30% males and 70% females. Regarding residence, all instructors are Alexandria residents. On the other hand, learners are 25% expatriates and 75% residents. Moreover, 78% of learners and 74% of instructors are registered in the field of social science.

6. Descriptive Analysis

This section includes the scoring and the multiple-response items' descriptive statistics for both instructors' and learners' models.

6.1. Instructors and Learners' Scoring

Firstly, the average score of the responses in each indicator is calculated. By the same token, the mean score of each construct is computed. Then, to perform this analysis, the following classifications are used for each range of scores, as depicted in Table 1.

Table 1

Scoring Range and Classification

Range	Agreement	Classification
4.21 – 5.00	Strongly Agree	Positive
3.41 – 4.20	Agree	

2.61 – 3.40	Neutral	Neutral
1.81 – 2.60 1.00 – 1.80	Disagree Strongly Disagree	Negative

Source: Authors' calculations for each range according to the following formula: $\frac{Max\ value\ of\ the\ scale - Min\ value\ of\ the\ scale}{number\ of\ groups\ (i.e.\ 5)}$.

Table 2 illustrates constructs' scoring for both stakeholders, while Tables A-1 and A-2 of Appendix A show the indicators' scoring. Regarding the net benefits, instructors agreed that they received high individual ($NB_{1:4}$) and societal impacts ($NB_{3,4}$) out of using the E-learning system. On the other hand, learners received moderate individual impacts ($NB_{1,2}$), yet they still believe that the E-learning system helps in achieving high societal impacts ($NB_{3,4}$). Hence, more concern should be given by the officials to improve the system to help raising learners' individual impacts.

Table 2

Constructs' Scoring and Classification

Constructs	Instructors		Learners	
	Constructs' Score	**Constructs' Classification**	**Constructs' Score**	**Constructs' Classification**
Net Benefits (NB)	3.70	Positive	3.38	Neutral
Technological Factors (TF)	3.72	Positive	3.33	Neutral
E-learning Quality (QU)	3.60	Positive	3.08	Neutral
User Attitude (UA)	3.33	Neutral	3.02	Neutral
Intention to Use (IU)	3.45	Positive	3.19	Neutral
User Satisfaction (US)	3.17	Neutral	2.86	Neutral

Source: Authors' calculations from Appendix A, Tables A-1, and A-2.

As seen from the mean score of the technological factors construct, instructors believe that they are provided with the suitable platform, infrastructure and assistance to cope with the E-learning process ($TF_{1,2,4}$). On the other side, students' responses revealed a neutral feedback regarding this construct. The low-quality of the available infrastructure in rural areas, the inadequate support, skills and financial capabilities of some students ($TF_{1:5}$) may be responsible for that result. Hence, the responsible authorities should upgrade infrastructure and may give learners more attention to equip them with the know-how and facilitate their E-learning experience by providing the needed support, training, devices and the internet packages required at a subsidized price.

Speaking about E-learning quality construct, instructors are positive towards the overall quality of the E-learning system ($QU_{2:5}$), except service quality (QU_1) they are neutral. Comparatively, learners have moderate verdict towards quality construct. Moreover, both users agree that other platforms, besides Microsoft Teams, may be needed for better communication and supervision over exams. Therefore, this raises an alert for officials about quality level delivered for students.

Having measured users' attitude toward the E-learning system, it was detected that their viewpoint toward the usage of technology in the educational process was neutral. Some learners could suffer from time-management problems due to "instructors' intrusions" outside the lecture's scheduled time, making students feel like it is "a nonending loop of assignments and lectures" ($UA_{1,3}$).

Regarding the intention to use construct, its score for the two studied groups shows that instructors are positively willing to utilize the online system in education, whilst learners have a moderate enthusiasm towards it. This may be because most students have neutral attitude concerning E-learning and their responses reveal a lack of motivation to engage in the online classes (IU_4). Besides, instructors find it hard to interact with their students adequately (IU_2). Therefore, officials should enhance the overall system to be more efficient and effective, subsequently, it will be reflected on stakeholders' attitude and increase their desire to reuse the system.

Likewise, tutors and students' answers about their level of satisfaction illustrate a neuter perception. This could be the result of learners' dependence on the recorded lectures, which has its advantages and disadvantages. Recorded lectures may encourage students to postpone studying, and prevent instructors from explaining the idea with a different way telling the students to "re-watch the lecture". These disadvantages may push learners to get private tutors for face-to-face learning due to the lack of face-to-face contact. Inspecting the score of that construct indicators for tutors manifested their dissatisfaction with students' attendance in the online lectures (US_2). As for learners' scores of the indicators ($US_{1:5}$), they were either negative or neutral, as most learners prefer the blended learning system to fully E-learning system. This may point out to the urge for enhancing some horizons of the online process such as better allowing students to follow class discussions, reinforcing peer-communication and consolidating student–teacher interaction.

6.2. Multiple-Response Descriptive Statistics

According to the responses of stakeholders, it was concluded that laptops and smartphones are the most frequently used devices in the E-learning process, representing 50% and 36% of instructors' usage respectively, meanwhile they constitute 36% and 55% of learners utilized-devices respectively.

Opinions of instructors and learners differ when providing and receiving material in the E-learning process. For instructors, the most preferred tools to provide educational materials are live online classes, then recorded classes, followed by PDF files and PowerPoint presentations. Moreover, they sometimes provide material as printed documents without records. For learners, the most frequently selected tools to receive their lectures are recorded classes, PDF files, live online classes, and PowerPoint presentations respectively.

Regarding the pros of using the E-learning system, both instructors and learners picked time and cost saving as the most acquired advantage of E-learning. Following, being accessible from any place was the second chosen benefit. Additionally, 12% and 10% of instructors' and learners' responses respectively show that the E-learning is generally a more efficient method for education. However, 4% of instructors as well as 17% of learners do not see any E-learning pros.

From the perspective of both instructors and learners, E-learning system may have some disadvantages, including; technical or internet connection problems, lack of social interaction and finally the disability to manage time properly. On the other side, 2% and 10% of instructors and learners respectively do not think that the E-learning system has any cons.

7. Results

In this section, Measurement model evaluation is performed to assess the reflective and formative models, then the structural model is evaluated for both stakeholders.

7.1. Measurement Models

7.1.1. Reflective Model Evaluation

Beginning with the reflective model, as illustrated in Table 3, reliability is evaluated by Cronbach's alpha (α) and CR, where their results indicate that reliability and internal consistency exist in the two models. Additionally, it is indicated that all reflective indicators have a satisfactory level of reliability, as their outer loadings exceed 0.708, except for (NB_1) in the instructors' model, which is greater than 0.40 and contributes to CR and AVE, therefore, no items will be eliminated. Moreover, the convergent validity is established for both models as the AVE values exceed 0.50.

Table 3

Outer Loadings, Reliability and Validity

Instructors					Learners				
Indicators	**Loading**	**α**	**CR**	**AVE**	**Indicators**	**Loading**	**α**	**CR**	**AVE**
Net Benefits									
NB1	0.63	0.84	0.88	0.55	NB1	0.76	0.81	0.88	0.64
NB2	0.72				NB2	0.77			
NB3	0.73				NB3	0.83			
NB4	0.76				NB4	0.84			
NB5	0.80								
NB6	0.81								
User Attitude									
UA1	0.79	0.74	0.85	0.66	UA1	0.79	0.80	0.88	0.71
UA2	0.80				UA2	0.84			
UA3	0.85				UA3	0.90			

Source: Authors' calculations for PLS-SEM results for measurement model evaluation.

The results of the cross loadings and Fornell-Larcker approaches are reported in Tables B-1, B-2, B-3 and B-4 of Appendix B and support the presence of the discriminant validity. In addition, HTMT ratios are calculated and their values show that $HTMT_{UA/NB}$ is less than 0.90 (Instructors' $HTMT_{UA/NB}$ = 0.718 and learners' $HTMT_{UA/NB}$ = 0.897) indicating that discriminant validity exists.

7.1.2. Formative Model Evaluation

The formative model is evaluated and the results state that convergent validity is established in all formative constructs in instructors' model; TF_{path}= 0.75, QU_{path} = 0.70, IU_{path} = 0.74, and US_{path}= 0.71. Regarding learners' model, convergent validity existed. For instance, TF_{path}= 0.71, QU_{path} = 0.83, IU_{path} = 0.73, and US_{path}= 0.80. As indicated in Table 4, all the outer weights' VIF values are less than 5, indicating that there is no high collinearity. Moreover, results indicate that all outer weights are statistically significant, except for QU_1 and QU_2 in the instructors' model, but their outer loading is greater than 0.50 (QU_1= 0.53 and QU_2= 0.76), hence, no items will be deleted (Hair et al., 2016).

Table 4

Indicators' Collinearity and Outer Weights

Instructors			Learners		
Indicators	**VIF**	**Outer Weight**	**Indicators**	**VIF**	**Outer Weight**
Technological Factors					
TF1	1.41	0.19*	TF1	1.61	0.09*
TF2	1.41	0.27**	TF2	1.96	0.12*
TF3	1.71	0.35***	TF3	1.44	0.27***
TF4	1.32	0.52***	TF4	2.09	0.32***
			TF5	1.82	0.46***
E-Learning Quality					
QU1	1.43	0.14	QU1	1.65	-0.07*
QU2	2.01	0.15	QU2	1.80	0.08*
QU3	1.77	0.28**	QU3	1.64	0.21***
QU4	1.32	0.31**	QU4	1.71	0.28***
QU5	1.37	0.51***	QU5	2.03	0.31***
			QU6	1.79	0.43***
Intention to Use					
IU1	1.43	0.27***	IU1	1.72	0.18***
IU2	1.28	0.37***	IU2	1.39	0.23***
IU3	1.46	0.61***	IU3	1.72	0.21***
			IU4	1.93	0.59***
User Satisfaction					
US1	1.21	0.18**	US1	2.23	0.19***
US2	1.31	0.30***	US2	1.90	0.19***
US3	1.60	0.31***	US3	1.93	0.20***
US4	1.75	0.51***	US4	2.39	0.25***
			US5	2.66	0.38***
*, ** and *** indicate significance at 10%, 5% and 1% respectively.					

Source: Authors' calculations for PLS-SEM results for measurement model evaluation.

7.2. Structural Models

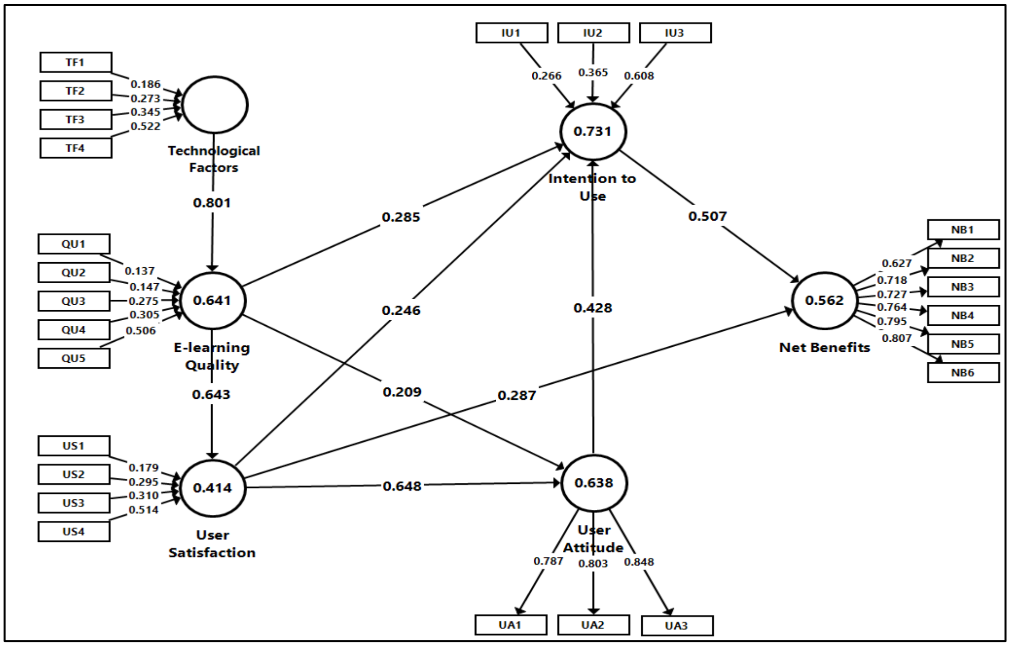
After ensuring measurment models' reliability and validity, structural models will be assessed.

7.2.1. Instructors' Structural Model

Figure 2 represents the instuctors' diagram, which shows the inner and outer relationships of the model.

Figure 2

Instructors' Model Diagram



Source: Authors' calculations for Instructors' PLS-SEM results for structural model evaluation.

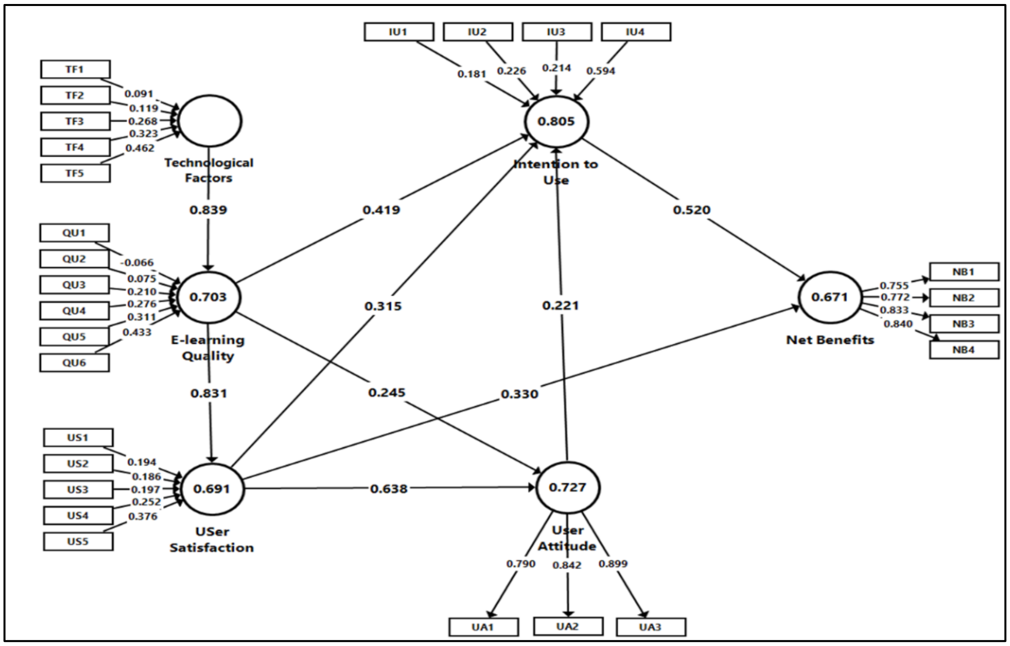
According to the VIF results depicted in Table 7, there is no collinearity problem among constructs. Moreover, all the previously mentioned hypotheses are supported as all the direct effects among the constructs are positive and statistically significant. H_1 is supported as technological factors ($\hat{\beta} = 0.80$) has a positive effect on E-learning quality, accounts for 64% of its variation. Moreover, H_{2A} is proved as E-learning quality ($\hat{\beta} = 0.64$) has a positive and significant impact on users' satisfaction and explains 41% of its variation. E-learning quality ($\hat{\beta} = 0.21$) as well as users' satisfaction ($\hat{\beta} = 0.65$) explain 64% of the variation of users' attitude with a positive effect on user's attitude, therefore, H_{2B} and H_{5B} are established. Regarding the intention to use, E-learning quality ($\hat{\beta} = 0.29$), users' satisfaction ($\hat{\beta} = 0.25$) and users' attitude ($\hat{\beta} = 0.43$) have a significant positive influence on intention to use and represent 73% of its variation, consequently, H_{2C}, H_{5A} and H_3 are supported. Finally, users' satisfaction ($\hat{\beta} = 0.29$) and intention to use ($\hat{\beta} = 0.51$) affect net benefits positively, where the model explains 56% of the net benefits' variation, therefore, H_{5C} and H_4 are indicated.

7.2.2. Learners' Structural Model

Figure 3 represents the learners' diagram, which shows the inner and outer relationships of the model.

Figure 3

Learners' Model Diagram



Source: Authors' calculations for learners' PLS-SEM results for structural model evaluation.

By evaluating learners' structual model, it is found that there is no collinearity problem among constructs as shown by Table 7. All the previously mentioned hypothese are proved, as all the direct relations among the constructs are positive and statistically significant. H_1 is supported as technological factors ($\hat{\beta} = 0.84$) has a positive impact on E-learning quality and interprets 70% of its variation. H_{2A} is also valid, where E-learning quality ($\hat{\beta} = 0.83$) has a statistically positive effect on users' satisfaction, accounts for 69% of its variation. E-learning quality ($\hat{\beta} = 0.25$) and users' satisfaction ($\hat{\beta} = 0.64$) jointly explain 73% of users' attiude with a statistically positive influence on users' attitude, hence, H_{2B} and H_{5B} are proved to be true. Talking about intetnion to use, E-learning quality ($\hat{\beta} = 0.42$), users' satisfaction ($\hat{\beta} = 0.32$) and users' attitude ($\hat{\beta} = 0.22$) have a significant positive effect on intention to use and represent 81% of its variation, therefore, H_{2C}, H_{5A} and H_3 are evidenced. Finally, users' satisfaction ($\hat{\beta} = 0.33$) and intention to use ($\hat{\beta} = 0.52$) have a significant positive influence on net benefits, where the model explains 67% of net benefits' variation, hence, H_{5C} and H_4 are supported.

7.2.3. Mediation Analysis Results

As illustrated in Table 5, the mediation effects in both models are significant. Hence, our findings provide empirical support for the mediating role of E-learning quality, user attitude, intention to use, and user satisfaction for the E-learning success in Egypt. As illustrated in figures 2 and 3, an enhancement in the technological factors will increase E-learning quality leading to an upsurge in users' satisfaction, attitudes and intention to use, which in turn raise users' precived attained net benefits of the E-learning system. Additionally, the total effects are not only significant but also mostly greater than 0.5 meaning that the constructs have moderate to high importance in the estimated models, hence officials should pay special attention to the constructs with the highest total effect for each stakeholder to improve the E-learning experience in Egypt. To determine the type of each mediation impact, we examined the theoritical and statistical significance of each direct and indirect relationships of the constructs. In both models, intention to use merely has a direct significant effect on net benefits, which probably explains the relationship between them as direct-only nonmediation (Hair et al., 2016). However, it supports the complete mediation of technological factors, E-learning quality and user attitude, and the partial mediation of user satisfaction.

Concerning the instructors' model mediation analysis results, it is indicated that constructs with the highest total effect on E-learning success are user satisfaction, E-learning quality, intention to use, technological factors, and user attitude in descending order. Therefore, increasing instructors' satisfaction by one standard deviation unit will improve the E-learning success by 0.56 standard deviation units. Thus, the attention should be given to the satisfaction dimensions and E-learning qulaity and technologicaol factors dimensions as improving their dimensions will enhance each constructs leading to a raise in their satisfaction and the subsequent constructs, which in turn will enhance the E-learning system success.

Table 5

Constructs' Total Indirect, Direct and Total Effect on Net Benefits

Constructs	Instructors			Learners		
	Total Indirect Effect	**Direct Effect**	**Total Effect**	**Total Indirect Effect**	**Direct Effect**	**Total Effect**
Technological Factors	0.44***	0.00	0.44***	0.60***	0.00	0.60***
E-learning Quality	0.55***	0.00	0.55***	0.72***	0.00	0.72***
User Attitude	0.22***	0.00	0.22***	0.12***	0.00	0.12***
Intention to Use	0.00	0.51***	0.51***	0.00	0.52***	0.52***
User Satisfaction	0.27***	0.29**	0.56***	0.24***	0.33***	0.57***
*, ** and *** indicate significance at 10%, 5% and 1% respectively.						

Source: Authors' calculations for bootstrapping results for the mediation analysis.

Regarding learners' model results, E-learning quality, technological factors, user satisfaction, intention to use, and attitude are ranked based on their importance to progress E-learning success. Thus, raising the E-learning quality by one standard deviation unit will increase the net benefits by 0.72 standard deviation units. Additionally, the officials' focus should be given to E-learning quality dimensions and technological factors' dimensions, as improving them will augment the E-learning quality which will be reflected to a higher satisfaction, attitude and intention to use the system and finally higher net benefits.

7.2.4. PLS Predict

$\mathrm{PLS}_{\mathrm{predict}}$ is undertaken to asses models' predictive power. First, the $\mathrm{Q}^2_{\mathrm{predict}}$ of the target construct and its indicators is assessed where their $\mathrm{Q}^2_{\mathrm{predict}}$ should be greater than zero to indicate that the PLS path model has predictive power. In instructors' model and learners' model, the net benefits' $\mathrm{Q}^2_{\mathrm{predict}}$ is 0.321 and 0.418, respectively. Moreover, as depicted in Table 6, the NB indicators achieve $\mathrm{Q}^2_{\mathrm{predict}}$ larger than zero for both models. Second, the distribution of the prediction errors of both models' indicators, resulted from the PLS path model, is nearly symmetric. Consequently, the subsequent analysis depends on the RMSE statistic. Ultimately, as stated priviously in the $\mathrm{PLS}_{\mathrm{predict}}$ guidelines, it is found that the instructors' model has medium predictive power, whereas the learners' model has low predictive power.

Table 6

PLS Predict Models' Results

Instructors				Learners			
Indicators	Q^2 Predict	RMSE		Indicators	Q^2 Predict	RMSE	
		PLS-SEM	LM			PLS-SEM	LM
NB1	0.142	0.969	0.989				
NB2	0.261	0.890	0.866	NB1	0.223	1.325	1.311
NB3	0.126	1.150	1.158	NB2	0.336	1.074	1.068
NB4	0.155	0.860	0.860	NB3	0.237	0.946	0.930
NB5	0.127	0.764	0.798	NB4	0.243	0.961	0.962
NB6	0.165	0.773	0.803				

Source: Authors' calculations for $\text{PLS}_{\text{predict}}$ models' results.

8. Discussion and Conclusion

As previously mentioned, the aim of this paper is to identify the CSFs of E-learning in Egypt based on data gathered from instructors and learners of tertiary education. To achieve this aim, the paper applies PLS-SEM approach using SmartPLS software. The models demonstrated a strong predictive power among all the constructs as they have explained on average 62%, 77%, 68%, 56% and 67% of the variation of net benefits, intention to use, users' attitude, satisfaction and E-learning quality respectively. The results also reveal that all the hypothesized relations for both models are empirically supported and are in line with the previous studies, as illustrated in Table 7.

Table 7

Significance of the Structural Model and Hypotheses.

Hypotheses	Literature Reference	Instructor		Learners	
		Coefficients	VIF	Coefficients	VIF
$\mathbf{H_1}$: TF → QU	(Makokha and Mutisya, 2016; Al-Azawei et al., 2016)	0.80***	1.00	0.84***	1.00
$\mathbf{H_{2A}}$: QU → US	(Ramayah and Lee, 2012)	0.64***	1.00	0.83***	1.00
$\mathbf{H_{2B}}$: QU → UA	(Xu et al., 2013; Abbas et al., 2016)	0.21**	1.71	0.25***	3.24
$\mathbf{H_{2C}}$: QU → IU	(Ramayah and Lee, 2012)	0.29***	1.83	0.42***	3.46
$\mathbf{H_3}$: UA → IU	(Davis, 1985; Liaw et al., 2007)	0.43***	2.76	0.22***	3.67
$\mathbf{H_4}$: IU → NB	(DeLone and Mclean, 2003)	0.51***	2.40	0.52***	3.60
$\mathbf{H_{5A}}$: US → IU	(Ramayah and Lee, 2012)	0.25***	2.86	0.32***	4.74
$\mathbf{H_{5B}}$: US → UA	(Xu et al., 2013)	0.65***	1.71	0.64***	3.24
$\mathbf{H_{5C}}$: US → NB	(Urbach et al., 2010)	0.29**	2.40	0.33***	3.60
*, ** and *** indicate significance at 10%, 5% and 1% respectively.					

Source: PLS-SEM results for Figure 2 and Figure 3.

This study found that technological factors positively influence E-learning quality (H_1), where good E-learning infrastructure, training and organizational support will improve ease of use and access to E-learning. Consequently, E-learning quality impacts user attitude positively (H_{2B}), where attitude is measured by perceived ease of use and utility dimensions. If users believe that they have a reliable high-quality system, the needed technical support and high information quality, their PU and PEOU will increase. As a result, users' attitude towards the system will be positive. Further, the results show that E-learning quality positively influences users' satisfaction (H_{2A}) and intention to use (H_{2C}). This finding can be explained from both perspectives; for learners, they seem to be satisfied with system flexibility and usefulness, sequentially, it motivates them to reuse the system. Similarly, for tutors, providing them with additional useful evaluation methods and facilitating the creation of new course designs will increase their satisfaction and intention to use the system. Subsequently, satisfaction is found to be positively impacting intention to use (H_{5A}). Since satisfaction reflects the system's usefulness, ease of use and users' attitudes, it can be deduced that increasing users' satisfaction will motivate them to reuse the system. Finally, Net Benefits is found to be positively influenced by intention to use (H_4) and user satisfaction (H_{5C}), as the increase in their satisfaction and intention to use the system will enrich their knowledge about its benefits, which will reflect on further increase in their performance, cost and time savings.

Furthermore, analyzing responses marked a crucial concern related to their perceptions about the selected E-learning aspects. Regarding E-learning benefits, it should help users manage their time properly and develop their skills. The scoring result does not support the latter finding, however, it indicates that E-learning assists in lessening traffic jam and environment pollution. Therefore, instructors should change course design to provide enjoyable and understandable content.

According to scores, the stakeholders suffer from learners' lack of readiness to use the system. Yet, such a problem has a higher effect on the tutors based on the PLS results indicating that the improvement of technological factors construct will enhance the E-learning quality. Hence, institutions should handle learners' disquiet needs by a comprehensive online and recorded workshops to raise their technological skills and their awareness about E-learning benefits, which will boost their satisfaction, intention to use and attitude towards E-learning.

The results revealed neutral feedback from tutors and students about the service quality. However, models' results depicted that such issue has an opposite effect on students due to the absence of personal attention when they experience problems. Tutors' answers also illustrate that using the E-learning increases their workload due to the lack of support. Therefore, technical support should be improved by providing trained IT personnel to guide the users and help them solve any technical issues, which could lead to raising the users' satisfaction due to enriching the E-learning quality.

Regarding user satisfaction, tutors complain from the students' online attendance, while students attribute their absence to many problems including tutors' inability to follow their progress in the educational process. The solution of this dilemma may be through appropriate trainings to tutors, as they are the main pillar for the E-learning success and they provide involvement incentives to the students. Hence, the users' satisfaction will increase, then, their attitude will be influenced positively. Finally, this positive attitude will stimulate users' intention to reuse the system.

Lack of proper interaction and communications are the E-learning vital problems. Therefore, stakeholders recommend blended learning, as it provides face to face interaction. Enhancing used platforms and stakeholders' communication, and scheduling special online lectures for students to discuss past materials and answer their questions will induce their intention to use the system because they will be able to ameliorate their skills and show their abilities to instructors.

Regarding the results of the mediation analysis for both models, policies should be targeting providing the required infrastructure, as well as a well-organized high-quality system, according to the users' needs, with better support to easily deal with the course content and enhance users' perceived usefulness. As a direct consequence, the increase in technological factors will involve an advance in the four mediators; E-learning quality, satisfaction, attitude and intention to use, which will reflect on E-learning success.

Ultimately, to get rid of the generalization limitations, further research should be applied for both models on wider ranges; places and times. Including more universities across Egypt, and/or including other countries in the sample is beneficial. Moreover, considering the importance of the time factor in affecting users' satisfaction and intention to use is of great importance.

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Appendix A

Table A-1

Indicators' Score of Instructors' Model

Indicators	Indicator's Score	Indicator's Classification

NB1: E-learning helps you to provide lessons in an appropriate time for you	3.77	**Positive**
NB2: Compared to traditional learning, E-learning leads to improve the level of your teaching	2.90	**Neutral**
NB3: Compared to traditional learning, your time can be better managed while teaching online	3.21	**Neutral**
NB4: E-learning cuts down expenditure (ex: transportation, paper cost, etc.)	4.02	**Positive**
NB5: E-learning helps in the mitigation of traffic jams	4.23	**Positive**
NB6: E-learning leads to less polluted environment	4.09	**Positive**
TF1: Your university has provided you with a training on how to use the E-learning platform	3.63	**Positive**
TF2: You have access to a reliable Internet connection in your home enough to teach online	4.12	**Positive**
TF3: Students at your university are ready to use technology for E-learning	3.28	**Neutral**
TF4: The E-learning platform is well-organized and easy to navigate and use	3.85	**Positive**
QU1: The responsible service staff provide personal attention when you experience problems (bugs, authorization problem, freeze) with the E-learning system	3.24	**Neutral**
QU2: The platform used fits the course criteria	3.95	**Positive**
QU3: The options provided by the chosen platform (electronic channels, access to library…etc.), facilitate the teaching process	3.60	**Positive**
QU4: The online courses' files are suitable for all device's student use	3.72	**Positive**
QU5: The content of the course is suitable to be introduced online	3.48	**Positive**
UA1: E-learning allows you to assign different tasks to the students which require external sources to solve it	3.37	**Neutral**
UA2: Even though it might not be required anymore you will continue to use the E-learning system	3.28	**Neutral**
UA3: By using the E-learning you can assess your student's performance through various ways (quizzes, written work, oral presentation, etc.)	3.35	**Neutral**
IU1: The university has the ability to switch to an E-learning system quickly	3.54	**Positive**
IU2: Most of students can interact freely with you in the online classes	3.26	**Neutral**
IU3: The E-learning system has multiple benefits which motivate you to continue using the system	3.54	**Positive**
US1: E-learning saves your teaching time	3.27	**Neutral**
US2: You feel satisfied with the attendance of the students in the online classes	2.52	**Negative**
US3: E-learning allows you to access more diverse student population	3.37	**Neutral**
US4: E-learning enables you to provide courses and tasks easier and more quickly	3.51	**Positive**

Source: Authors' calculations

Table A-2

Indicators' Score of Learners' Model

Indicators	**Indicator's Score**	**Indicator's Classification**
NB1: Using E-learning system helps you to cut down expenditure such as paper costs	3.03	**Neutral**
NB2: Compared to traditional learning, E-learning leads to improve the level of your understanding	2.60	**Negative**
NB3: E-learning helps in the mitigation of traffic jams	4.02	**Positive**
NB4: E-learning leads to less polluted environment	3.87	**Positive**
TF1: Your university has provided you with a training on how to use the E-learning platform	2.85	**Neutral**
TF2: The platform used fits the course criteria	3.50	**Positive**
TF3: You have access to a reliable Internet connection in your home enough to learn online	3.73	**Positive**
TF4: The university has the ability to switch to an E-learning system quickly	3.07	**Neutral**
TF5: The E-learning platform is well-organized and easy to navigate and use	3.51	**Positive**
QU1: The responsible service staff provide personal attention when you experience problems (bugs, authorization problem, freeze) with the E-learning system	3.01	**Neutral**
QU2: Instructors at your university are well-prepared to use the E-learning platforms	3.02	**Neutral**
QU3: The online courses' files are suitable for all devices you use	3.44	**Positive**
QU4: The variety of ways to assess your learning is effective in evaluating your academic level	3.10	**Neutral**
QU5: The options provided by the chosen platform (electronic channels, access to library…etc.), facilitate the E-learning process	3.34	**Neutral**
QU6: Compared to traditional learning, the quality of education has increased through E-learning	2.58	**Negative**

UA1: E-learning has a positive impact on your sleep pattern compared to traditional learning	2.88	**Neutral**
UA2: Even though it might not be required anymore you will continue to use the E-learning system for self-learning	3.05	**Neutral**
UA3: Your mental health enables you to adapt E-learning system	3.13	**Neutral**
IU1: Your online skills have improved due to E-learning	3.02	**Neutral**
IU2: The E-learning offers a variety of ways to assess your learning (ex: quizzes, written work, oral presentation, etc.)	3.55	**Positive**
IU3: You want to do well in your E-learning classes because it's important to show your abilities to your instructors, family and colleagues	3.08	**Neutral**
IU4: The E-learning system has multiple external benefits which motivate you to continue using the system	3.12	**Neutral**
US1: It was easy to follow class discussions through the platform	2.95	**Neutral**
US2: Compared to traditional learning, instructor is able to follow with your individual learning progress through the E-learning platform	2.36	**Negative**
US3: You learned more from your fellow students in E-learning system than in traditional learning	2.60	**Negative**
US4: Compared to traditional learning, your time can be better managed while learning online	3.13	**Neutral**
US5: E-learning platform enables you to accomplish tasks easier and more quickly	3.26	**Neutral**

Source: Authors' calculations

Appendix B

Table B-1

Instructors' Model Cross Loadings

	QU	IU	NB	TF	US	UA
NB1	0.411	0.408	**0.627**	0.426	0.450	0.321
NB2	0.650	0.677	**0.718**	0.595	0.618	0.608
NB3	0.555	0.574	**0.727**	0.383	0.522	0.469
NB4	0.430	0.451	**0.764**	0.422	0.444	0.336
NB5	0.451	0.513	**0.795**	0.388	0.458	0.394
NB6	0.484	0.527	**0.807**	0.445	0.452	0.402
UA1	0.486	0.563	0.430	0.393	0.611	**0.787**
UA2	0.543	0.713	0.557	0.423	0.626	**0.803**
UA3	0.494	0.662	0.442	0.440	0.669	**0.848**

Source: Authors' calculations

Table B-2

Instructors' Model Fornell-Larcker Criterion

	QU	IU	NB	TF	UA
IU	0.710				
NB	0.687	0.726	**0.742**		
TF	0.801	0.671	0.608		
US	0.643	0.764	0.674	0.559	0.782
UA	0.626	0.798	0.589	0.516	**0.813**

Source: Authors' calculations

Table B-3

Learners' Model Cross Loadings

	QU	IU	NB	TF	US	UA
NB1	0.518	0.609	**0.755**	0.477	0.558	0.521
NB2	0.765	0.725	**0.772**	0.602	0.725	0.696

NB3	0.540	0.581	**0.833**	0.495	0.557	0.543
NB4	0.561	0.620	**0.840**	0.502	0.599	0.570
UA1	0.599	0.570	0.516	0.474	0.667	**0.790**
UA2	0.614	0.707	0.647	0.546	0.693	**0.842**
UA3	0.744	0.765	0.693	0.641	0.770	**0.899**

Source: Authors' calculations

Table B-4

Learners' Model Fornell-Larcker Criterion

	QU	**IU**	**NB**	**TF**	**UA**
IU	0.853				
NB	0.758	0.800	**0.801**		
TF	0.839	0.724	0.655		
US	0.831	0.850	0.772	0.731	0.842
UA	0.776	0.812	0.738	0.661	**0.845**

Source: Authors' calculations