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Investigating Critical Success Factors of E-Learning: Different Stakeholders' Perspectives

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The educational process has been hindered worldwide due to Covid-19 pandemic. Yet, the Egyptian government adopted E-learning to maintain the designed educational agenda. Consequently, recognizing E-learning benefits is imperative to link the E-learning system with its success drivers. Therefore, the aim of this study is detecting the main critical success factors that affect E-learning in Egypt. The study employed multiple information system success models as a basis for identifying aspects of E-learning success measured by net benefits, namely; technological factors, E-learning quality, user attitude, intention to use and user satisfaction. Online questionnaires were directed to two stakeholder groups of tertiary education, namely; learners and instructors. Using partial least squares structural equation modeling technique, the two models were statistically confirmed. The results indicate that the E-learning success models adequately demonstrate and predict the interdependency of the selected constructs. Moreover, the importance-performance map analysis was implemented to investigate the importance and performance of the constructs and indicators on E-learning success. This analysis identified user satisfaction and E-learning quality as the most crucial constructs for achieving higher success in both models. Furthermore, users' perceived usefulness, ease of use and information quality are indicators that should be improved to indirectly foster E-learning success.

Keywords: information system success model, e-learning success, Egypt, partial least square (PLS), importance and performance map analysis (IPMA), critical success factors (CSFs)

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).

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Unfortunately, the outbreak of the COVID-19 pandemic has hindered the educational process. Yet, the Egyptian government has planned to continue the educational process by 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 has created many challenges for all stakeholders including learners and instructors, therefore universities started to provide training for them 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 & Seaman, 2014). In fact, E-learning system provides many benefits as: saving costs and time, 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, as encouraging students' indolence, lack of communication among stakeholders, platforms usage illiteracy, and increasing system's maintenance costs (Batdı, Doğan, & Talan, 2021). In contrast, 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 & Seaman, 2014).

Despite the rapid adoption of E-learning, one of the main issues facing officials is reinforcing its success. Therefore, the objectives of this paper are investigating the instructors and learners' opinions on the current E-learning system shortcomings through the scoring technique, in addition to determining the main Critical Success Factors (CSFs) which influence E-learning in Egypt. Furthermore, the study aims to determine which CSF is the most important factor for the policymakers to have a major impact on improving the E-learning system from both stakeholders' perspectives. Finally, this paper seeks to examine the reliability, validity and out-of-sample predictive power for a comprehensive framework, that includes instructors and learners' models to be used in evaluating E-learning success in future research as well. 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), as well as the previous studies on Egypt.

Additionally, this paper is the first in Egypt that 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. Further, most researchers ignore some sophisticated techniques as: Importance-Performance Map Analysis (IPMA), and depend only on the PLS analysis. However, IPMA helps providing more rigorous recommendations for decision makers to refine the net benefits. In addition, $\mathrm{PLS}_{\mathrm{predict}}$ is applied to measure models' predictive power.

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

Review of Literature

Past researches highlighted the importance of determining the CSFs that influence E-learning adaptation and resulting net benefits (Sun, Tsai, Finger, Chen, & Yeh, 2008). 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 E-learning systems improvements. Leidecker and Bruno (1984) defined CSFs as constructs, characteristics or circumstances that would have a significant influence on a project's success.

The Information System success (ISS) model presented by D&M is a predominant dimensional model for evaluating an operational ISS. According to its most updated version of 2003, several dimensions are included to evaluate E-learning success. These dimensions are system, service and information qualities, intention to use, satisfaction and net benefits. Net benefits are considered a comprehensive measure which includes interorganizational, consumer, work group and societal impacts according to Clemons, Reddi, and Row (1993), Brynjolfsson (1996), Myers, Kappelman, and Prybutok (1997), and Seddon (1997) respectively.

Reviewing the studies of Egypt, it was detected that the education system suffers from many challenges; overcrowded classes, transportation issues and innovation in programs and courses (El Gamal, 2014). Therefore, Egypt has an urgent need to implement E-learning to mitigate the conventional education problems. Additionally, the literature about E- learning implementation and the most important CSFs in Egypt using different methodologies is presented as an important issue to develop E-learning.

Utilizing Confirmatory Factor Analysis approach, Headar, Elaref, and Yacout (2013) and Abbas, Jones, & Hussien (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 and cost savings.

In 2011, Eraqi, Abou-Alam, Belal, and Fahmi conducted descriptive analysis and stated that E-learner, E-instructor, IT, university factors and E-learning quality are the most important CSFs of the E-learning. Using the same technique, others deduced that many users accepted E-learning as an effective instrument for education. However, large number of students believe that it is challenging to interact with others, especially as most of the users suffer from poor computer skills. Consequently, they recommended that blended learning should be applied to provide the most efficient level of learning and get over the lack of skills (Abdelaziz, Kamel, Karam, & Abdelrahman, 2011; Khedr, 2012; El-Seoud, El-Sofany, Taj-Eddin, Nosseir, & El-Khouly, 2013; Ghenghesh, Croxford, Nagaty, & Abdelmageed, 2018).

METHOD

In this section, the constructs, hypotheses of the models and the techniques used to analyze them are illustrated.

Research Variables and Hypotheses

Upon reviewing the relevant literature, additionally, inspired by the updated D&M model (2003), the paper used NB as a measure for E-learning success (Hassanzadeh, Kanaani, & Elahi, 2012)., Technological Factors (TF), E-Learning Quality (QU), User Attitude (UA), Intention to Use (IU) and User Satisfaction (US) are selected as potential CSFs of E-learning in Egypt.

As a promising gauge for the E-learning success, NB is 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, organizations and even societies (DeLone & McLean, 2003; Hassanzadeh et al., 2012). Consequently, in this study, NB are represented by improving users' performance, cost and time savings (Parker & Martin, 2010), less polluted environment and smooth flow of traffic (Campbell & Campbell, 2011).

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 & Munro, 2008). According to Bhuasiri, Xaymoungkhoun, Zo, H., Rho, and Ciganek (2012), TF is one of the CSFs in both developed and developing countries. Moreover, Makokha and Mutisya (2016) claimed that shortage of devices and inadequate internet would affect the E-learning system negatively.

Several dimensions were taken into consideration to quantify TF such as the Country's infrastructure and medium richness. A 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' training (Arbaugh & Duray, 2002), while medium richness refers to platforms' ability to support various types of instructional elements (text, audio and video messages) (Volery & Lord, 2000).

To sum up, countries should pay special attention to TF to enhance the QU especially developing countries due to their technological challenges ensuring the ease of access to the system and its success (Al-Azawei, Parslow, & Lundqvist, 2016). Therefore, it's proposed that:

H_1: TF has a direct positive effect on QU.

E-learning Quality

Based on prior studies, quality construct can be measured by three quality types; system, service and information qualities. They play a key role in determining users' behaviors, therefore, in this study, QU was measured in terms of the previously mentioned qualities types as dimensions. System quality is a multi-dimensional concept representing the hardware and software qualities available to the end-users to fulfill their information needs (Poelmans & Wessa, 2015). Additionally, service quality is the quality of the support provided to users by service providers (Petter & McLean, 2009; Hassanzadeh et al., 2012). Finally, information quality represents the quality of the course content that is introduced by the providers and delivered by the system. It also refers to the improvements in users' performance through using the system (Bhuasiri et al., 2012).

Previous studies indicate that if users believe that the system's performance is reliable, technical support is available, and the available information is accurate, they will realize the usefulness of the E-learning system and its ease of use. Consequently, this will affect UA and US with the system positively, as well as motivating them to reuse E-learning (DeLone & McLean, 2003; Ramayah & Lee, 2012; Xu, Benbasat, & Cenfetelli, 2013; Abbas et al., 2016). Hence, the following hypotheses will be empirically tested:

H_{2A}: QU has a direct positive effect on US.

H_{2B}: QU has a direct positive effect on UA.

H_{2C}: QU has a direct positive effect on IU.

Attitude

Users' attitude represents the users' positive or negative psychological state to perform a certain behavior, such as using the E-learning system (Abdel-Wahab, 2008).

Using the TRA, Davis (1985) introduced the TAM with two concepts to measure UA which leads to behavioral intention; the Perceived Usefulness (PU), which is 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 UA. This paper is based on the Rosenberg model, which reflects UA by their PU from the system usage and how using it is important for them.

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

H_3: UA has a direct positive effect on IU.

Intention to Use

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

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 as improving their skills. Therefore, having the IU system would directly affect the NB (DeLone & Mclean, 2003). Accordingly, the following hypothesis is tested:

H_4: IU has a direct positive effect on NB.

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.

Satisfaction concept may differ according to different perspectives. Regarding learners, Arbaugh (2000) identified four dimensions, which are; platform flexibility, usability, PU and interactive environment. Besides, Bolliger and Wasilik (2009) determined three dimensions influencing instructors' satisfaction; student-related, instructor-related and institution-related dimensions.

US will be positively influenced, if users are provided with training and support. Furthermore, if they are satisfied with the E-learning, they will have a positive attitude towards it and their intention to reuse it will increase. Further, being satisfied will provide a high level of benefits to users leading directly to success (Urbach, Smolnik, & Riempp, 2010). Therefore, the following hypotheses are assessed:

H_{5A}: US has a direct positive effect on IU.
H_{5B}: US has a direct positive effect on UA.
H_{5C}: US has a direct positive effect on NB.

Partial Least Square Model

The Structural Equation Modelling (SEM) is a vital tool of multivariate statistical analysis for testing hypotheses to analyse the structural theory of a given phenomenon (Hair, Hult, Ringle, & Sarstedt, 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.

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.

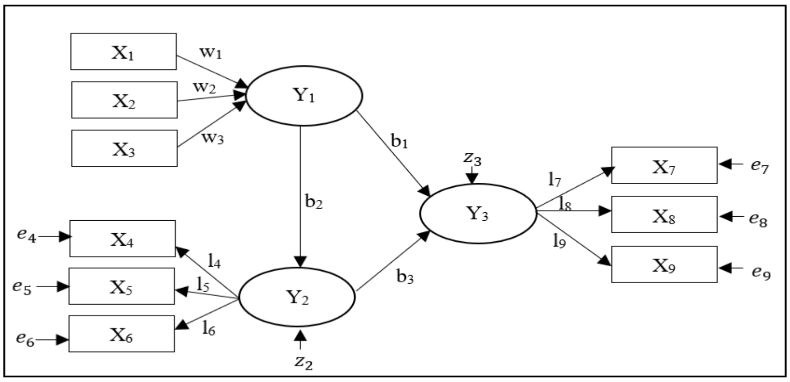

Figure 1
PLS-SEM path model

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.

$$X = lY + e \text{.........} \quad (1)$$

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).

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

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, Ringle & Hair, 2021).

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).

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).

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

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.

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

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).

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

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 $\varnothing_{ij}^2$. Therefore, the discriminant validity is established only if the AVE is greater than $\varnothing_{ij}^2$, 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^2 value 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).

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 $\mathrm{PLS}_{\mathrm{predict}}$. According to Shmueli et al. (2019), researchers should undertake two steps to deploy $\mathrm{PLS}_{\mathrm{predict}}$. 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.

Importance-Performance Map Analysis

The IPMA is mainly valuable for providing further insights by combining the analysis of the importance and performance dimensions of the PLS-SEM models' constructs, which allows for prioritizing certain constructs to improve the key target construct (Ringle & Sarstedt, 2016). The importance dimension refers to the constructs' total effects on the target construct, whereas the performance dimension indicates the average construct scores after being rescaled on a range from 0 to 100. The IPMA combines these two dimensions graphically by contrasting the unstandardized total effects on the x-axis, with the rescaled constructs scores on the y-axis. Additionally, to analyze the importance-performance map, researchers add two additional lines; a vertical line exhibiting the mean importance value and a horizontal line exhibiting the mean performance value. These lines divide the importance-performance map into four-quadrants, where constructs in the lower right quadrant are of the highest interest to achieve improvement, as these constructs have relatively high importance and low performance, followed by the constructs in the higher right, lower left and, finally the higher left quadrants. Thus, the results are particularly vital in forming recommendations by measuring the impacts that different constructs have on E-learning success.

Data

Data were collected through anonymous online questionnaires using Google Forms, administrated to two stakeholder groups; instructors and learners at higher education institutions in Alexandria, Egypt during the second semester of 2021. Appendix A presents both questionnaires which are based upon previous literature and consist of Likert scale questions. The five-point Likert scale questions range from 1 to 5, where 1 is assigned to strongly disagree and 5 to strongly agree, and 3 was the neutral point of view. These questionnaires were statistically analysed by the SmartPLS 3 software (V. 3.3.3). A total of 100 valid instructors' responses were collected, including 33% male and 67% females, while 320 students have responded including 30% males and 70% females. All instructors are residents while, only 75% of learners are residents. Moreover, 78% of learners and 74% of instructors are registered in the social science field.

Descriptive Analysis

This section includes the scoring results for the indicators and constructs of both models. Firstly, the average score of the responses in each indicator is calculated then used to compute the constructs' mean score. Finally, the following classifications depicted in Table 1 are used.

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	Disagree	Negative
1.00 – 1.80	Strongly Disagree	

Table 2 illustrates constructs' scoring for both stakeholders, while Tables A-1 and A-2 of Appendix A show the indicators' scoring. Regarding the NB, instructors agreed that they received high individual ($NB_{1:4}$) and societal impacts ($NB_{3,4}$) out of using the system. Contrastingly, learners received moderate individual impacts ($NB_{1,2}$), and 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	
	Score	Classification	Score	Classification
NB	3.70	Positive	3.38	Neutral
TF	3.72	Positive	3.33	Neutral
QU	3.60	Positive	3.08	Neutral
UA	3.33	Neutral	3.02	Neutral
IU	3.45	Positive	3.19	Neutral
US	3.17	Neutral	2.86	Neutral

According to the mean score of the TF in table 2, instructors believe that they are provided with the suitable platform, infrastructure and assistance to cope with the E-learning ($TF_{1,2,4}$). However, 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 provide learners with the needed support, training, devices and the internet packages.

Speaking about QU, instructors are positive toward it ($QU_{2:5}$), 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 UA toward the E-learning, it was detected that their viewpoint toward the usage of technology in the educational process was neutral. Some learners 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 IU, its score for the users shows that instructors are positively willing to utilize the E-learning system, whilst learners have a moderate enthusiasm. 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 system to be more efficient and effective, subsequently, it will be reflected on stakeholders' attitude and IU.

Likewise, stakeholders' answers about their 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. Inspecting the score of that construct indicators for tutors manifested their dissatisfaction with students' attendance (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 to fully E-learning. This may point out to the urge for enhancing some horizons of the online process such as better peer and student-teacher interaction.

FINDINGS

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

Measurement Models

Reflective Model Evaluation

Beginning with the reflective model, as illustrated in Table 3, construct reliability, which demonstrates the stability and compatibility of the measurements, is evaluated by Cronbach's alpha (α) and Composite Reliability (CR). The results indicate that the reliability exists in the two models, as the coefficient of both α and CR are greater than 0.60. Further, all reflective indicators have a satisfactory reliability level, as their loadings exceed 0.708, except for (NB1) in the instructors' model, which is greater than 0.40 and contributes to CR, hence, no items will be removed. The convergent validity, that exists when indicators of a certain construct share a high proportion of variance, is established for both models as the Average Variance Extracted (AVE) values exceed 0.50.

Table 3
Loadings, reliability and validity

Instructors					Learners				
Indicators	Loading	α	CR	AVE	Indicators	Loading	α	CR	AVE
Net Benefits									
NB_1	0.63								
NB_2	0.72				NB_1	0.76			
NB_3	0.73	0.84	0.88	0.55	NB_2	0.77	0.81	0.88	0.64
NB_4	0.76				NB_3	0.83			
NB_5	0.80				NB_4	0.84			
NB_6	0.81								
User Attitude									
UA_1	0.79				UA_1	0.79			
UA_2	0.80	0.74	0.85	0.66	UA_2	0.84	0.80	0.88	0.71
UA_3	0.85				UA_3	0.90			

Regarding the discriminant validity, which means that each construct captures different phenomena from other constructs, the cross loadings and Fornell-Larcker approaches are performed and support the presence of it, Heterotrait-Monotrait (HTMT) ratios are less than 0.90 (instructors' HTMTUA/NB = 0.718 and students' HTMTUA/NB = 0.897) indicating that discriminant validity exists (Hair et al., 2016).

Formative Model Evaluation

Concerning the formative model, convergent validity, that is examined by redundancy analysis, refers to the extent to which an indicator contributes to the actual meaning of its construct. The results state that convergent validity is established as the path coefficients between the formative and the reflective of the same construct at least equals 0.70, 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 exists as follows, 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 $QU_{1,2}$ in the instructors' model, but their loadings are greater than 0.50 (QU_1=0.53 and QU_2=0.76), hence, no items will be deleted (Sarstedt et al., 2021).

Table 4
Indicators’ collinearity and weights

Instructors			Learners		
Indicators	VIF	Weight	Indicators	VIF	Weight
Technological-Factors					
TF_1	1.41	0.19*	TF_1	1.61	0.09*
TF_2	1.41	0.27**	TF_2	1.96	0.12*
TF_3	1.71	0.35***	TF_3	1.44	0.27***
TF_4	1.32	0.52***	TF_4	2.09	0.32***
			TF_5	1.82	0.46***
E-Learning-Quality					
QU_1	1.43	0.14	QU_1	1.65	-0.07*
QU_2	2.01	0.15	QU_2	1.80	0.08*
QU_3	1.77	0.28**	QU_3	1.64	0.21***
QU_4	1.32	0.31**	QU_4	1.71	0.28***
QU_5	1.37	0.51***	QU_5	2.03	0.31***
			QU_6	1.79	0.43***
Intention-to-Use					
IU_1	1.43	0.27***	IU_1	1.72	0.18***
IU_2	1.28	0.37***	IU_2	1.39	0.23***
IU_3	1.46	0.61***	IU_3	1.72	0.21***
			IU_4	1.93	0.59***
User-Satisfaction					
US_1	1.21	0.18**	US_1	2.23	0.19***
US_2	1.31	0.30***	US_2	1.90	0.19***
US_3	1.60	0.31***	US_3	1.93	0.20***
US_4	1.75	0.51***	US_4	2.39	0.25***
			US_5	2.66	0.38***

*, ** and *** indicate significance at 10%, 5% and 1% respectively.

Structural Models

After ensuring measurement models’ reliability and validity, structural models will be assessed.

Instructors’ Structural Model

Figure 2 represents the instructors’’ model diagram, which shows the inner and outer relationships. According to the VIF results depicted in table 6, there is no multi-collinearity among constructs. Moreover, all the previously mentioned hypotheses are supported as all the direct effects among the constructs are positive and significant.

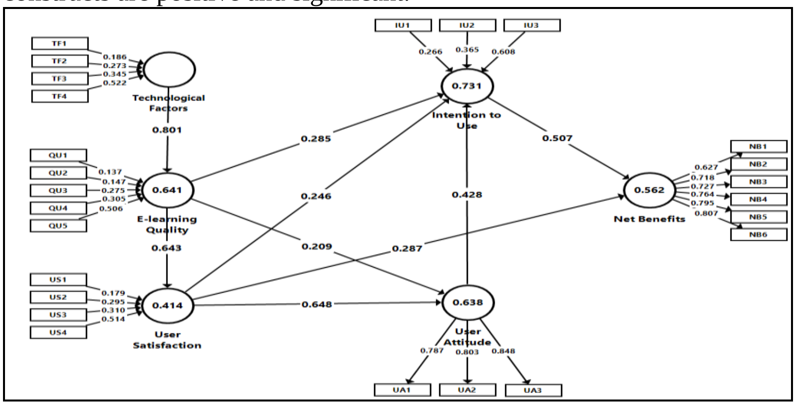

Figure 2
Instructors’ model diagram

H_1 is supported as TF ($\hat{\beta} = 0.80$) has a positive effect on QU, accounting for 64% of its variation. Moreover, H_{2A} is proved as QU ($\hat{\beta} = 0.64$) has a positive and significant impact on US and explains 41% of its variation. QU ($\hat{\beta} = 0.21$) and US ($\hat{\beta} = 0.65$) explain 64% of the variation of UA with a positive effect on user's attitude, therefore, H_{2B} and H_{5B} are established. Regarding the IU, QU ($\hat{\beta} = 0.29$), US ($\hat{\beta} = 0.25$) and UA ($\hat{\beta} = 0.43$) have a significant positive influence on IU and represent 73% of its variation, consequently, H_{2C}, H_{5A} and H_3 are supported. Finally, US ($\hat{\beta} = 0.29$) and IU ($\hat{\beta} = 0.51$) affect NB positively, where the model explains 56% of the NB variation, therefore, H_{5C} and H_4 are indicated.

Learners' Structural Model

Figure 3 represents the learners' diagram. By evaluating learners' structural model, it is found that there is no multi-collinearity among constructs as shown by Table 6. All the hypotheses are proved, as all the direct relations among the constructs are positive and significant.

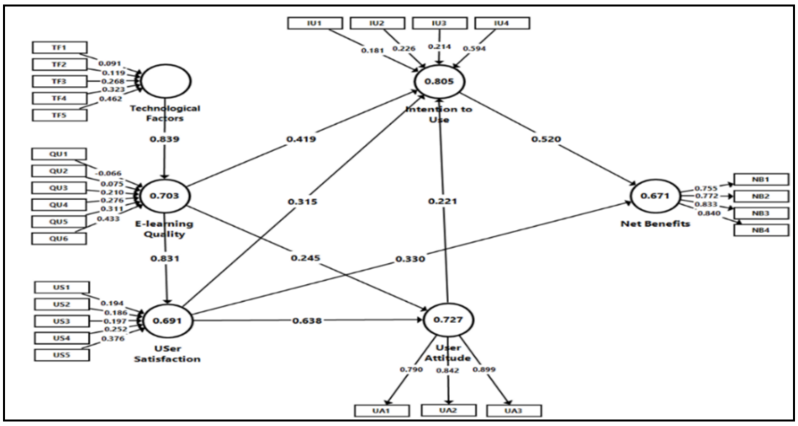

Figure 3
Learners' model diagram

H_{2A} is also valid, where QU ($\hat{\beta}$=0.83) has a statistically positive effect on US, accounts for 69% of its variation. QU ($\hat{\beta}$=0.25) and US ($\hat{\beta}$=0.64) jointly explain 73% of UA with a statistically positive influence on UA, hence, H_{2B} and H_{5B} are proved to be true. Talking about IU, QU ($\hat{\beta}$=0.42), US ($\hat{\beta}$=0.32) and UA ($\hat{\beta}$=0.22) have a significant positive effect on IU and represent 81% of its variation, therefore, H_{2C}, H_{5A} and H_3 are evidenced. Finally, US ($\hat{\beta}$=0.33) and IU ($\hat{\beta}$=0.52) have a significant positive influence on NB, where the model explains 67% of NB variation, hence, H_{5C} and H_4 are supported.

PLS Predict

$\text{PLS}_{\text{predict}}$ is undertaken to asses models' predictive power in two steps. First, the $Q^2_{predict}$ of the target construct 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. In instructors and learners' model, the NB $Q^2_{predict}$ is 0.321 and 0.418, respectively. Moreover, as depicted in Table 5, its indicators achieve $Q^2_{predict}$ larger than zero for both models.

Table 5

$\textbf{PLS}_{\textbf{predict}}$ Models' Results

Instructors				Learners			
Indicators	$Q^2_{predict}$	RMSE PLS-SEM	RMSE LM	Indicators	$Q^2_{predict}$	RMSE PLS-SEM	RMSE LM
NB_1	0.142	0.969	0.989	NB_1	0.223	1.325	1.311
NB_2	0.261	0.890	0.866	NB_2	0.336	1.074	1.068
NB_3	0.126	1.150	1.158	NB_3	0.237	0.946	0.930
NB_4	0.155	0.860	0.860	NB_4	0.243	0.961	0.962
NB_5	0.127	0.764	0.798				
NB_6	0.165	0.773	0.803				

Second, the degree of prediction error should be evaluated either using the Mean Absolute Error (MAE) when the prediction error distribution is highly asymmetric or using the Root Mean Squared Error (RMSE) otherwise. As both models' prediction error distribution is nearly symmetric, the subsequent analysis depends on the RMSE statistic. According to Shmueli et al. (2019), the model has low predictive power if the minority of indicators have lower prediction errors while, it has medium predictive power if most indicators have lower prediction errors. Therefore, it is concluded that the learners' model has low predictive power and the instructors' model has medium predictive power.

Importance-Performance Map Analysis Results

Concerning instructors' IPMA results, as depicted in Figure 4, it is indicated that constructs with the highest priority for raising E-learning success are US, QU, TF, IU, and UA, descendingly. Further, the results demonstrate that NB performance equals 67.53. Therefore, increasing the performance of satisfaction by one unit will increase the NB performance by 0.46 points. Thus, to improve the E-learning success, the priority should be given to US dimensions and its predecessors (QU and TF) dimensions. Thereupon, the platform's usefulness, which enables tutors to teach in creative ways, has a relatively high importance, then, information quality and the availability of platforms significantly support the E-learning process.

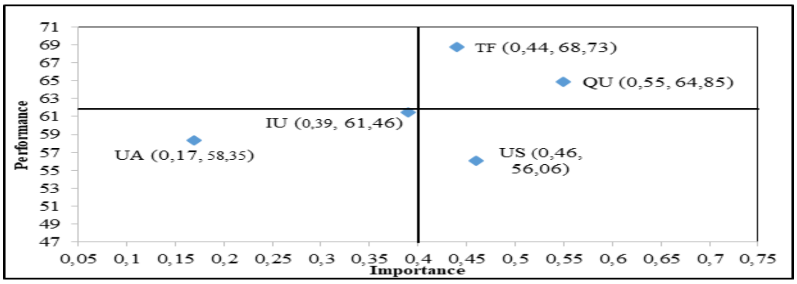

Figure 4
Instructors' IPMA

Regarding learners' IPMA results, as depicted in Figure 5, QU, US, TF, UA, and IU are prioritized according to the highest interest in boosting E-learning success. In addition, the results indicate that net benefit has a performance value equals 60.09. Hence, raising the performance of QU by one unit will rise the NB performance by 0.71 points. Additionally, to increase the E-learning success, the interest should be given to QU dimensions and its predecessor (TF) dimensions. Subsequently, the quality of education, the platform's usefulness and ease of use dimensions have a relatively high importance.

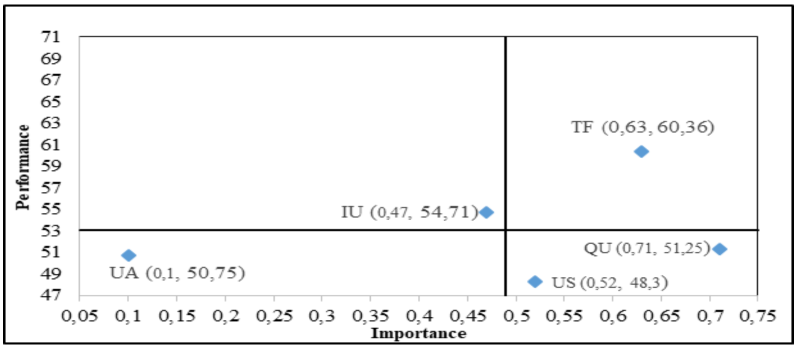

Figure 5
Learners' IPMA

DISCUSSION, CONCLUSION AND SUGGESTIONS

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. Accordingly, this paper applies PLS-SEM approach using SmartPLS software. The models demonstrated strong predictive power among all the constructs as they have explained on average 62%, 77%, 68%, 56% and 67% of the variation of NB, IU, UA, US and QU, 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 6.

Table 6
Significance of the structural model and hypotheses

Hypotheses	Literature Reference	Instructor		Learners	
		Coefficients	VIF	Coefficients	VIF
H_1: TF → QU	(Makokha & Mutisya, 2016; Al-Azawei et al., 2016)	0.80***	1.00	0.84***	1.00
H_{2A}: QU → US	(Ramayah & Lee, 2012)	0.64***	1.00	0.83***	1.00
H_{2B}: QU → UA	(Xu et al., 2013; Abbas et al., 2016)	0.21**	1.71	0.25***	3.24
H_{2C}: QU → IU	(Ramayah & Lee, 2012)	0.29***	1.83	0.42***	3.46
H_3: UA → IU	(Davis, 1985; Liaw et al., 2007)	0.43***	2.76	0.22***	3.67
H_4: IU → NB	(DeLone & Mclean, 2003)	0.51***	2.40	0.52***	3.60
H_{5A}: US → IU	(Ramayah & Lee, 2012)	0.25***	2.86	0.32***	4.74
H_{5B}: US → UA	(Xu et al., 2013)	0.65***	1.71	0.64***	3.24
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 Figure 2 and Figure 3

This study found that TF positively influence QU (H_1), where good infrastructure, training and organizational support will improve ease of use and access to E-learning. Consequently, QU impacts UA positively (H_{2B}), where UA is measured by PEOU and PU dimensions. If users believe that they have a reliable high-quality system, the needed technical support and high information quality, UA towards the system will be positive. Further, the results show that QU positively influences US (H_{2A}) and IU (H_{2C}). From learners' perspective, 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 course designs will increase their satisfaction and IU. Subsequently, US is found to be positively impacting IU (H_{5A}). Since US reflects the system's usefulness, ease of use and UA, it can be deduced that increasing US will motivate them to reuse the system. Finally, NB is found to be positively influenced by IU (H_4) and US (H_{5C}), as the increase in US and IU will enrich their knowledge about its benefits, reflecting on further increase in their performance and time saving.

Furthermore, analyzing responses marked a crucial concern related to stakeholders' perceptions about the selected E-learning aspects. Regarding E-learning benefits, it should help users in time management and skills improvement. 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, stakeholders suffer from learners' lack of readiness towards system. Yet, such a problem has higher effects on the tutors based on the PLS results indicating that the improvement of TF will enhance QU. Hence, institutions should handle learners' disquiet needs by a comprehensive online and recorded workshops to raise their technological skills and awareness about E-learning benefits, which will boost their satisfaction, intention to use and attitude towards E-learning.

The results revealed neutral feedback from users about 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 illustrate that using E-learning increases their workload due to the lack of support. Therefore, technical support should be improved by providing trained IT personnel to guide users and solve technical issues, which could lead to raising US due to enriching QU.

Regarding US, 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 students. Hence, US will increase, then, UA will be influenced positively. Finally, this positive attitude will stimulate users' IU E-learning.

Regarding the results of IPMA for both models, officials' policy should be in providing well-organized high-quality system that facilitate usage and navigation, easily deal with the course content and enhance users' PU. As a direct consequence, the performance of TF and QU increase, which involve and entail an improvement in US and the target key construct E-learning success. Consequently, if the E-learning system shortcomings were addressed, highly self-regulated learners would show significantly more positive attitudes toward E-learning in the future. However, Hanif (2020) showed that low self-regulated learners would tend to continue having negative attitudes toward using E-learning.

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 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 is the first in Egypt that adopts the PLS-SEM technique to investigate E-learning success. Furthermore, the IPMA is conducted to assist officials in setting better priorities and to allocate scarce resources efficiently through identifying the construct, which has the highest importance and performance for the NB. Additionally, the paper utilizes $\mathrm{PLS}_{\mathrm{predict}}$ to evaluate the model's out-of-sample predictive power. Despite the importance of the IPMA and $\mathrm{PLS}_{\mathrm{predict}}$, few papers utilized them in the E-learning literature (Ringle & Sarstedt, 2016; Sarstedt et al., 2021).

Current findings point to some important implications that could be summed up as follows. Blended learning seems to be the solution for some of the previously mentioned problems facing the current E-learning system; as it provides partial face-to-face learning, which is helpful for improving learners' body language, social interaction, presentation skills, and for better delivering and understanding of the course materials. Moreover, it overcomes some conventional education problems, such as overcrowded classes, and transportation issues. Blended learning is proven to be an effective way for self-regulated learners, who systematically manage their learning process to attain their personal goals, to continue their education in the future (Bahri, Idris, Muis, Arifuddin & Fikri, 2021). Additionally, enhancing used platforms and scheduling special online lectures for students, to discuss past materials and answer their questions, will induce their willingness to continue using the system, because they will be able to ameliorate their skills and show their abilities to instructors.

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, especially underdeveloped and developing countries due to their lacking in resources, training and infrastructure compared to developed nations. Moreover, considering the importance of the time factor in affecting user satisfaction and intention to use the E-learning system is of great importance.

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APPENDIX A

Table A-1
Indicators' Score of Instructors' Model

Indicators	Score	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	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	3.28	Neutral
UA3: By using the E-learning you can assess your student's performance through various ways	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 several benefits which motivate you to continue using it	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

Table A-2
Indicators' Score of Learners' Model

Indicators	Score	Classification
NB1: Using E-learning system helps you to cut down expenditure such as paper costs	3.03	Neutral
NB2: Compared to traditional, 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	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	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 several external benefits which motivate you to continue using it	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		Negative
US4: Compared to traditional learning, your time can be better managed while learning online	2.60	Neutral
US5: E-learning platform enables you to accomplish tasks easier and more quickly	3.1	Neutral

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