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Factors affecting the E-learning acceptance: A case study from UAE

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Abstract
The main objective of this article is to study the factors that affect university students' acceptance of E-learning systems. To achieve this objective, we have proposed a new model that aims to investigate the impact of innovativeness, quality, trust, and knowledge sharing on E-learning acceptance. Data collection has taken place through an online questionnaire survey, which was carried out at The British University in Dubai (BUiD) and University of Fujairah (UOF) in the UAE. There were 251 students participated in this study. Data were analyzed using SmartPLS and SPSS. The Structural Equation Modelling (SEM) has been used to validate the proposed model. The outcomes revealed that knowledge sharing and quality in the universities have a positive influence on E-learning acceptance among the students. Innovativeness and trust were found not to significantly affect the E-learning system acceptance. By identifying the factors that influence the E-learning acceptance, it will be more useful to provide better services for E-learning. Other implications are also presented in the study.

Keywords E-learning · Technology acceptance · Knowledge sharing · Technology innovativeness · System quality · Trust

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1 Introduction

Due to the significant improvements in the domain of Information and Communication Technology (ICT) (Al-Emran and Malik 2016; Skersys et al. 2011; Al Emran and Shaalan 2014a; Al-Emran and Salloum 2017), there have been revolutionary changes in acquiring information through different time-efficient strategies. Keeping in view the significant growth and developments, several learners are now attracted towards educational activities that adopt modern technology and electronic resources (Alkandari 2015; Liu et al. 2010). The education sector calls for adopting ICT tools at various phases of the education process and for implementing a novel learning strategy. Hence, professionals in the field of education are attracted to various inventions in the ICT world, so that they can adopt them in teaching and learning activities. Several universities all over the world have accepted E-learning for encouraging and improving learning; meanwhile, supporting lifelong learning. The latest innovations in ICT, along with the improvements in Internet infrastructure and the extensive use of the World Wide Web have taken E-learning to a new level which make E-learning more flexible, interactive and well designed (Alkandari 2015). In the UAE, the Ministry of Education has especially acknowledged the potentially critical role of ICT in the growth of the teaching and learning process (Fook et al. 2015). Major higher institutions for education in the UAE, such as the University of Fujairah and the British University in Dubai, have started including ICT by following an integrated approach, where different ICT tools are made part of the learning process. The Blackboard and Moodle are ones of such software tools that represent efficient learning management systems for enhancing the learning process.

Nonetheless, different factors are involved in determining the success of such environments and these factors need to be taken into account to create a successful and effective E-learning system. After initial experiences, most of the learners do not persist with their E-learning courses. Hence, it is vital to comprehend the factors involved such that the learner does not have a "passive experience, which leads to surface learning" (Alkandari 2015). In addition, these factors may have an impact on the learners' acceptance, readiness, and decision-making with respect to adopting E-learning on the long run. Hence, when a novel E-learning environment or ICT tool is presented in the learning process, it is highly important for the institutions and instructors to show their willingness in using these systems in order to encourage the students to fully accept and use them. The success of E-learning systems (Kanwal and Rehman 2017) will eventually depend on the degree of the learner acceptance and the application of these systems (Van Raaij and Schepers 2008). Lee (2006) considers external factors affect the E-learning acceptance. Hence, these factors should be investigated and grouped in accordance with their significance. The main aim of this study is to examine the factors affecting the E-learning acceptance in the UAE educational environment.

The structure of this research is as follows: section 2 presents a comprehensive background and a summary of the literature review pertaining to the E-learning system acceptance and the research model of this study is demonstrated in section 3. Section 4 presents the methodology that directs the research. Section 5 presents the analysis of data collection and findings. Discussion, research implications, limitations and further research are addressed in section 6. Finally, the key findings and conclusion are presented in section 7.

2 Literature review

Nowadays, educational technologies have quickly evolved along with the prompt development of ICTs (Al-Emran and Shaalan 2015, 2017; Salloum et al. 2017). The last two decades have witnessed an increase in the prevalence of the internet due to the reason that universities and other educational institutions have made investments in information systems (like Moodle, Blackboard) so as to help in face-to-face as well as distant course delivery (Tarhini et al. 2013). Using E-learning along with networked computers facilitates transmitting the digitized knowledge from the online sources to the final user devices, like a laptop, desktop and handheld devices (Misra et al. 2014; Behera 2013). The perception of the users, their competencies, and computer use knowledge determines the successful implementation of E-learning systems (Lee et al. 2013). In the previous studies, E-learning acceptance is viewed from the technological, organizational, and environmental perspective (Jaradat 2014; Abu-Al-Aish and Love 2013).

Campbell and Ma (2015) found acceptance of e-textbooks influenced by technology innovativeness and system exposure. Perceived usefulness is the most important factor that influences the students' acceptance and intent to adopt E-learning systems in the higher education in Kuwait (Alkandari 2015). In Sri Lanka, significant impact of observability and comparative advantage on attitude and intent to use E-learning exists (Yatigammana et al. 2013). Effort expectancy, performance expectancy, social influence, and facilitating conditions had a statistically significant impact on students' acceptance of using mobile learning solutions in the higher education of East Africa (Mtebe 2014).

There are significant positive impacts of perceived usefulness and perceived ease of use on E-learning acceptance (Chen and Tseng 2012). The knowledge sharing behavior play a critical role in E-learning system acceptance (Eid and Al-Jabri 2016). The knowledge sharing behavior (KSB) is positively related to academic self-efficacy (ASE), and sense of community (SoC) of university students in E-learning community (Yilmaz 2016). Quality is another factor that has been found to influence the acceptance and adoption of E-learning technology (Adel 2017). The system quality attributes have a vital role in providing user satisfaction to keep on using E-learning system (Mahmodi 2017; Dreheeb et al. 2016; Rodríguez and Meseguer-Artola 2016). The users will not use the system if its quality is poor (Liao and Huang 2009), and this will let them to refuse adopting the system (Chou et al. 2012).

The trust has strong positive effects on student's behavior towards E-learning (Alkhalaf et al. 2012; Tarhini et al. 2016). A number of studies have been conducted on students trust in the past in different countries (Tarhini et al. 2016; Wang 2014; Chang and Lee 2013; Liu and Wu 2010). The selected studies carried out on E-learning acceptance that adopt different research models are described in Table 1.

According to the surveyed literature, it has been observed that there is a few number of studies that examined the factors that affect the E-learning acceptance in the UAE. Consequently, this study attempts to propose a new model that aims to examine the effect of innovativeness, quality, trust, and knowledge sharing on the students' acceptance of E-learning.

Table 1 A summary of elearning acceptance studies

Study	IS application	Samples	Identified factors
Mahmodi (2017)	E-learning system	124 university students	Perceived ease of use, perceived usefulness, and attitude.
Dečman (2015)	E-learning system	228 university students	The social influence and performance expectancy have a significant impact. The students' past education and gender has no significant impact.
Yee-Loong Chong et al. (2014)	E-business	168 Malaysian SMEs.	The knowledge acquisition and knowledge application have a significant impact while knowledge dissemination did not have a significant impact.
Cakir and Solak (2014)	E-learning system	231 male and 279 female e-language learners.	The attitude, ease of use, self-efficacy, and satisfaction showed a positive effect on the academic success of e-learners.
Abu-Al-Aish and Love (2013)	M-learning system	174 participants	The effort expectancy, performance expectancy, the influence of lecturers, personal innovativeness, and quality of service all play a significant role in influencing the behavioral intention to adopt m-learning.
Tarhini et al. (2013)	E-learning system	569 undergraduate and postgraduate students	The perceived ease of use, perceived usefulness, quality of work life, and social norms influence the students' behavioral intention.
Farahat (2012)	Online learning system	153 undergraduate students	The usefulness, ease of use, attitudes, and social influence were all significant factors that affect the students' intention to take part in online learning.

3 Research model

The factors that may influence users' acceptance of E-learning can be grouped under four constructs (Masa'd 2017; Purnomo and Lee 2013). The correlation between innovativeness and E-learning acceptance was examined using the basic model, where the impact of knowledge sharing, trust, and quality of this relationship was investigated. Various online courses are offered by the E-learning system in Fujairah University (UOF) and The British University in Dubai (BUiD), and these are available through Moodle and Blackboard. Hence, the objective of this study is to determine the effect of the constructs discussed earlier regarding behavior intention to adopt E-learning (Robinson 2014). Fig. 1 provides an illustration of the proposed research model.

3.1 Technology innovativeness

Innovation consist of competitive advantage, observability, complexity, and variability (Ngafeeson and Sun 2015). According to Ngafeeson and Sun (2015), technology innovativeness (TI) had a significantly positive impact on perceived usefulness (PU) and behavioral intention (BI). There is a significant association between technology innovativeness and perceived ease of use (EOU) (Joo et al. 2014). According to these findings, students' willingness to use new information technologies plays a significant part in use decisions in full implementation (higher system exposure) settings (Tarhini et al. 2016). Therefore, TI will possibly be a significant factor that determines intent to use. The previous studies performed on innovativeness and E-learning acceptance showed positive relationship. The hypothesis given below is hence developed:

Hypothesis 1. Innovativeness has a positive effect on E-learning acceptance.

3.2 Knowledge sharing

In any information system, knowledge sharing is also a significant component (Migdadi et al. 2016). There is better creativity, and ultimately, better performance at the individual as well as organizational level. This is why all universities give importance to knowledge sharing between students and teachers. Besides, knowledge sharing

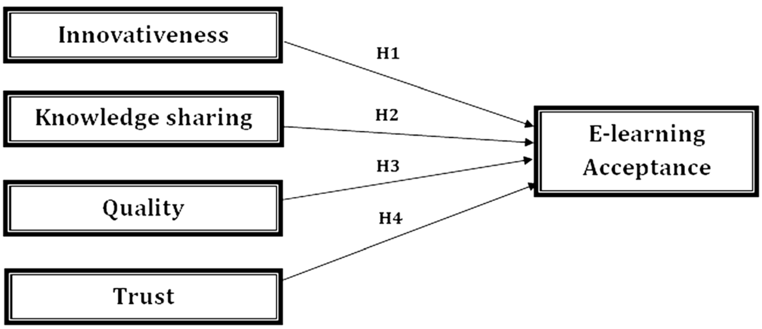

Fig. 1 The proposed conceptual framework

is regarded as the key component of knowledge management (Al Emran and Shaalan 2014b). Knowledge sharing is especially important in virtual teams, where assessing the associated factors is critical. The main aspect that influences students' learning and performance in virtual teams is the social collaboration among team members. Purnomo and Lee (2013) examined the effect of knowledge sharing on E-learning system acceptance. It is likely that knowledge distribution positively affects the adoption of E-learning technology. Thus, the following hypothesis is formulated:

Hypothesis 2. Knowledge Sharing has a positive effect on E-learning acceptance**.**

3.3 Quality

The degree to which an industry describes a group of required features that should be included in the product to improve its lifetime performance is known as system quality (Dreheeb et al. 2016). The Information System Model considers system quality to be a critical success factor that affects user satisfaction and the intent to use (Delone and McLean 2003). It has been determined that the system quality being given to individual users positively and significantly influence the way they perceive and behave with respect to the acceptance and adoption of new technological inventions (Faqih 2016). Furthermore, it has been found in studies that a key reason for losses and extensive dropout rates in the field of E-learning is the low perceived quality of E-learning systems (Faqih 2016; Wu and Zhang 2014). Quality service has also been considered to positively affect the behavioral intent of students and teachers to implement E-learning technology. Hence, the hypothesis given below is developed:

Hypothesis 3. Quality has a positive effect on E-learning acceptance.

3.4 Trust

The trust is defined as "the readiness of an individual to accept vulnerability on the basis of positive expectations regarding the intentions or behavior of another person in the context of risk and interdependence" (El-Masri and Tarhini 2017). The student trust is significant in E-learning course acceptance (Wang 2014). Trust has been given a lot of attention, directly as well as indirectly, in the past studies on technology adoption and acceptance (Al-rahmi et al. 2015; Luo et al. 2010). However, as trust is not the same for every country and technology, the hypothesis given below will be examined:

Hypothesis 4. Trust has a positive effect on E-learning acceptance.

4 Research methodology

The results from data analysis will be elaborated in this section. Firstly, the demographic factors of the survey respondents are given. Next, the methods and technology applied by the respondents are presented. Thirdly, the choice of data analytic technique is described. Fourthly, the findings obtained from the analysis of the measurement model (Calvo-Mora et al. 2005) are presented. Finally, the findings from the analysis of the structural model are given, in addition to the analysis of the tests of hypothesis.

4.1 Sample and study instrument

Data collection has taken place through an online questionnaire survey, which was carried out at The British University in Dubai (BUiD) in the Emirate of Dubai, and University of Fujairah (UOF) in the Emirate of Fujairah, in the UAE. The study is carried out on a total of 311 students, out of which 251 surveys were completed, while 60 surveys were not considered due to the respondent's inability to finish the questionnaires. A survey instrument was created to test the hypothesis given in this research. For measuring the five constructs in the questionnaire, 15 items were included in the survey.

Al-Emran et al. (2016) stated that the "purposive sampling approach" is an easy approach to reach the participants; the reason that motivated us to use this approach. The study sample included students from different colleges, studying at different levels and belonging to different age groups. Demographic data was tested using IBM SPSS Statistics ver. 23. Of the 251 respondents, 112 (45%) were males and 139 (55%) were females. The respondent ages ranged from approximately 18 years to 59 years and above. 48% were between the ages of 18 and 29; 39% were between ages of 30 and 39; 11% were between ages of 40–49; 6% were between ages of 50–59. Examination of age category indicates that the sample has slightly younger respondents. The analysis of the respondent colleges indicates that 29% of the respondents from the college of business administration and 30% from the college of engineering and Information Technology. Both college of mass communication and relations, and college of general education for 34% of the total respondents. While 7% for the college of art, social sciences and humanities. The majority of the respondents are well-educated and have university degrees. 38% individuals had a master degree, 35% had a bachelor degree, 12% had a doctoral degree with the rest having some diploma, diploma/advanced or secondary school education. About 30% of the respondents lived in the Emirate of Fujairah, and 27% of the respondents lived in Dubai. While Abu Dhabi, Sharjah, Ajman, Umm Al-Quwain, and Ras Al-Khaimah have only 43% of the total respondents. Around 81% of the respondents used intranet including home, university, and Internet subscription connection. 17% of the respondents reported using the home connection, while 14% reported using University, 4% reported using the Internet subscription connection to use the Internet. Likewise, 57% of the respondents used Blackboard E-learning system, while 43% reported using Moodle E-learning system.

4.2 Survey structure

An online questionnaire survey has been prepared and distributed among the students. The online survey consists of six sections. The first section includes the personal data of the participants in addition to their access to the internet usage. The second section consists of five items that represents questions about the E-learning system. The third section consists of three items that represent E-learning system quality. The fourth section includes three items that represent sharing knowledge through E-learning. The fifth section consists of two items that represent trust. Finally, the last section consists of three items that represent innovativeness. A five-point *Likert Scale* with very satisfied (5), somewhat satisfied (4), neither satisfied nor dissatisfied (3), somewhat dissatisfied (2), and very dissatisfied (1) has been used to measure the items.

5 Findings and discussion

A significant role will be played by E-learning in developing teaching and learning methods for higher education. Nonetheless, E-learning can only be successfully applied to higher education when there is user acceptance for this technology. Therefore, this study aims to examine the factors that influence the intent of university students to accept E-learning.

5.1 Assessment of the measurement model (outer model)

The association between the indicators and latent construct being measured are described by the measurement model. Two kinds of validities are needed for evaluating the measurement model (Roky and Al Meriouh 2015); convergent validity and discriminant validity (Hair et al. 2016). The extent to which there is a high correlation between theoretically identical constructs is suggested by convergent validity. On the other hand, the extent to which a certain construct differs from other constructs is given by discriminant validity (Rahman et al. 2013). These two validities together offer some proof of the goodness of fit of the measurement model (Joo et al. 2014).

5.1.1 Convergent validity

Two methods were used to examine convergent validity. Firstly, the loadings of the individual measures to their corresponding constructs (Ashill and Jobber 2010) were examined, and secondly, the composite reliabilities were determined. Convergent validity was tested using Partial Least Squares (SmartPLS ver. 3.2.6). Two different analyses were performed. The preliminary PLS operation through boot strapping process (300 resamples) produced loadings, weights, average variance extracted (AVE), composite reliabilities and t-values for every measurement item corresponding to its theorized construct. Analysis of the loadings for every measurement item was performed. It was found that the loadings of all items were more than the suggested value of 0.70 (Hair et al. 2016).

The loadings for the measurement items are found to be a lot higher than the suggested value of 0.70 or more (Kundu and Gahlawat 2016). It is suggested by item loadings of 0.70 or more that over 50% of the variance is divided between the measurement item and its hypothesized construct (Barclay et al. 1995). The consequent number of items for each construct, average variance extracted and composite reliabilities (Vinzi et al. 2010) is presented in Table 2. There is good internal consistency because the composite reliability values are more than 0.80 (Nunnally and Bernstein 1994). Table 2 shows that composite reliability values are in the range of 0.853 to 0.920, which is over the suggested value of 0.80, while most of them are more than 0.90.

Table 2 Results of measurements model - convergent validity

Constructs	Items	Loading	AVE	CR
Quality	Quality_1	0.847	0.764	0.906
	Quality_2	0.869		
	Quality_3	0.905		
Knowledge Sharing	KS_1	0.882	0.784	0.916
	KS_2	0.889		
	KS_3	0.885		
Trust	Trust_1	0.898	0.814	0.897
	Trust_2	0.906		
Innovativeness	Inovativeness_1	0.894	0.793	0.920
	Inovativeness_2	0.895		
	Inovativeness_3	0.882		
E-learning Acceptance	Gen_E_Colleeagues	0.846	0.793	0.853
	Gen_E_Easy	0.771		
	Gen_E_Feedback	0.805		
	Gen_E_Subject	0.807		

*Factor Loadings >(0.7), Composite reliability >(0.7), AVG > (0.5)

5.1.2 Discriminant validity

The degree to which one construct differs from all other constructs in the research model (Matias-Reche et al. 2008) is ascertained through discriminant validity (Chin 1998). Discriminant validity was examined using two processes. The correlations of the latent variable measurements with the measurement items were analyzed. Discriminant validity could be determined by making the measures of constructing different. The measures should show powerful loading on their hypothesized construct instead of the other constructs in the research model. This means that the loadings should be higher compared to the cross loadings (Hair et al. 2016).

The average variance extracted (AVE) is assessed to make certain that every construct has a larger variance with its measures compared to the other latent constructs in the research model (Storey and Kahn 2010). Generally, the square root of the AVE for a particular construct should be a lot greater compared to the variance shared among the construct and other constructs within the model (Hair et al. 2016; Chin 1998), and it should be more than the given value of 0.5 (Fornell and Bookstein 1982). When the AVE value is more than 0.5, it is suggested that the construct constitutes a minimum of 50% of the measurement variance. The discriminant validity was assessed using the Fornell-Larcker scale and cross-loadings. The Fornell-Larcker scale analysis is given in Table 3. The square root of the AVE scores (Abu-Al-Aish 2014) is given by the bold diagonal elements in the table. In contrast, the off-load diagonal elements represent the correlations between the constructs. The values of cross-loadings are given in Table 4. A study of the loadings and cross-loadings shows that the measurement items all load extensively on their own latent constructs instead of loading on other constructs (Cheng and Chen 2015).

Table 3 Results of discriminant validity – Fornell-Larcker scale

Variable	E-learning Acceptance	Innovativeness	Knowledge Sharing	Quality	Trust
E-learning Acceptance	**0.808**				
Innovativeness	0.601	**0.890**			
Knowledge Sharing	0.684	0.768	**0.885**		
Quality	0.758	0.672	0.682	**0.874**	
Trust	0.639	0.785	0.836	0.710	**0.902**

5.2 Assessment of structural model (inner model)

After determining the suitability of the measurement model (Harun et al. 2015), the structural model was examined, and the hypothesis was tested. It is suggested by the structural model that there is a causal relationship between the latent constructs of the research model. The structural model was first assessed by identifying the predictive power of the model and then, by assessing the hypothesized associations between the latent constructs suggested in the research model (Hair et al. 2016). The predictive power of the research model is determined by the R-square value of the dependent variables, while the capacity of the hypothesized relations is analyzed using the path coefficients. PLS-Graph Version 3.0 was used to perform validation of the structural model. The model was included in PLS according to the directions presented in the PLS-Graph Users Guide. The outcomes of the PLS-Graph output are given in Fig. 2.

Table 4 Results of discriminant validity – cross loadings

Items	Quality	Knowledge Sharing	Trust	Innovativeness	E-learning Acceptance
Quality_1	**0.847**	0.559	0.589	0.571	0.649
Quality_2	**0.869**	0.589	0.607	0.575	0.618
Quality_3	**0.905**	0.636	0.661	0.615	0.715
KS_1	0.651	**0.882**	0.746	0.735	0.587
KS_2	0.580	**0.889**	0.733	0.643	0.608
KS_3	0.582	**0.885**	0.742	0.664	0.620
Trust_1	0.656	0.788	**0.898**	0.711	0.565
Trust_2	0.625	0.723	**0.906**	0.705	0.586
Inovativeness_1	0.612	0.693	0.673	**0.894**	0.558
Inovativeness_2	0.623	0.673	0.733	**0.895**	0.522
Inovativeness_3	0.560	0.684	0.692	**0.882**	0.523
Gen_E_Colleeagues	0.662	0.503	0.471	0.434	**0.846**
Gen_E_Easy	0.567	0.531	0.454	0.470	**0.771**
Gen_E_Feedback	0.606	0.654	0.647	0.561	**0.805**
Gen_E_Subject	0.612	0.516	0.484	0.474	**0.807**

p<0.1

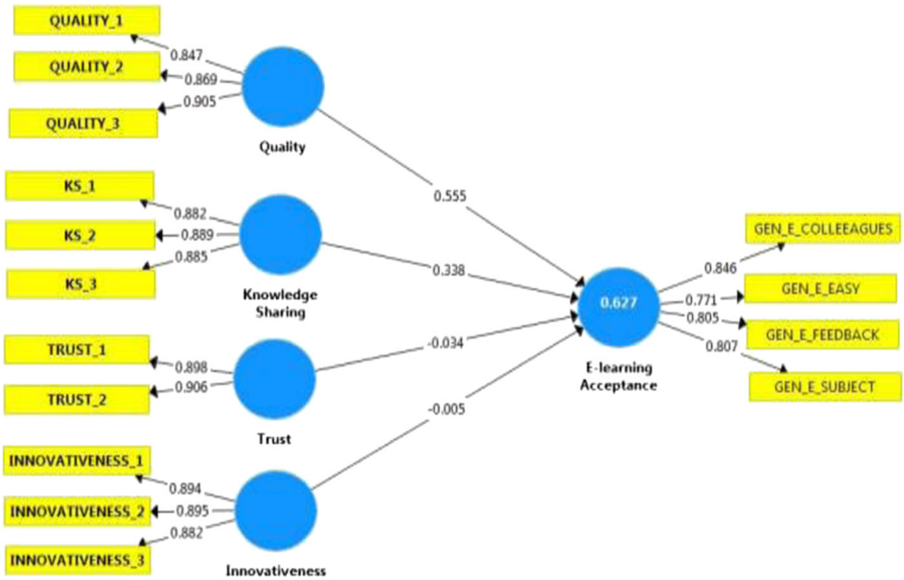

Fig. 2 Predictive power of the model

5.2.1 Coefficient of determination (R^2)

The structural model is usually examined using the coefficient of determination (R^2 value) measure Dreheeb et al. (2016). This coefficient is used to determine the predictive accuracy of the model (Roky and Al Meriouh 2015) and is computed as the squared correlation between a particular endogenous construct's actual and predicted values (Senapathi and Srinivasan 2014). The exogenous latent variables' combined impact on the endogenous latent variable is signified by the coefficient. The coefficient is the squared correlation between the actual and predicted values (Hair et al. 2016; Senapathi and Srinivasan 2014); hence, it also signifies the extent of variance in the endogenous constructs justified by every exogenous construct related to it. According to Chin (1998), when the R^2 value is more than 0.67, it is perceived as high, whereas the values in the range of 0.33 to 0.67 are moderate and the values in the range of 0.19 to 0.33 are weak. In addition, when the value of R^2 is lower than 0.19, it is unacceptable. An R-squared value of 0.10 has been suggested by Falk and Miller (1992) as a minimum acceptable level.

5.2.2 Effect size

The relative effect of a specific exogenous latent variable on the endogenous latent variable(s) through the variations in the R-squared value is given by the effect size (Abbas et al. 2017; Hair et al. 2016). It is computed as the rise in the R-squared value of the latent variable to which the path is linked, comparative to latent variable's percentage of unexplained variance (Abbas et al. 2017; Chin 1998).

As shown in Table 5, the value of f^2 was evaluated by Cohen (1988) and Bakeman (2005) criteria. The exogenous constructs C1, C2, C3, and C4 (see Table 6) for explaining the endogenous latent variable C5 have $f2$ effect sizes of 0.000, 0.080,

Table 5 Effect size criteria

f^2	Result
Above 0.35	Large effect size
Ranging from 0.15 to 0.35	Medium effect size
Between 0.02 to 0.15	Small effect size
Less than 0.02	No effect size

0.372 and 0.001, respectively. Hence, the effect size of construct C1 on the endogenous latent variable C5 has no effect, the size effect of construct C2 on the endogenous latent variable C5 is small, and construct Y3 has a medium effect size. Finally, the effect size of construct C4 on the endogenous latent variable C5 has no effect size.

5.2.3 Predictive relevance

Apart from assessing the R^2 values as a determinant of predictive accuracy, researchers also need to assess the Stone-Geisser's Q^2 value (Geisser 1974; Stone 1974), which is representative of the predictive relevance of the model. To be more specific, when predictive relevance is shown by PLS-SEM, then it precisely predicts the data points of indicators in reflective measurement models of endogenous constructs and endogenous single-item constructs (Senapathi and Srinivasan 2014). The Q^2 values in the structural model that is larger than zero for a particular reflective endogenous latent variable show the path model's predictive relevance for this specific construct. A measure of predictive ability is needed to use PLS for prediction (Hair et al. 2016). The Blind folding procedure is the method put forward to assess predictive relevance (Senapathi and Srinivasan 2014). Out of all the latent variables, knowledge sharing, innovativeness, trust, and quality were discovered to be significant. When there was an omission distance of 7, a Q^2 value of 0.377 was obtained in the study, which suggests that there is a highly predictive model (see Fig. 3 and Table 7). It is suggested by this outcome that prediction of observables or possible observables has a lot more relevance compared to predicting what are frequently unreal construct parameters (Akter et al. 2011; Geisser 1974).

5.2.4 Goodness of fit the model

Gof was described by Tenenhaus et al. (2005) as the global fit measure, which is the geometric mean of average variance extracted (AVE) as well as the average of R2 of the endogenous variables (Hair et al. 2016). Gof essentially seeks to assess the study model

Table 6 Interpreting effect size - f^2

Construct Code	Construct	f^2	Result
C1	Innovativeness	0.000	No effect size
C2	Knowledge Sharing	0.080	Small effect size
C3	Quality	0.372	Large effect size
C4	Trust	0.001	No effect size

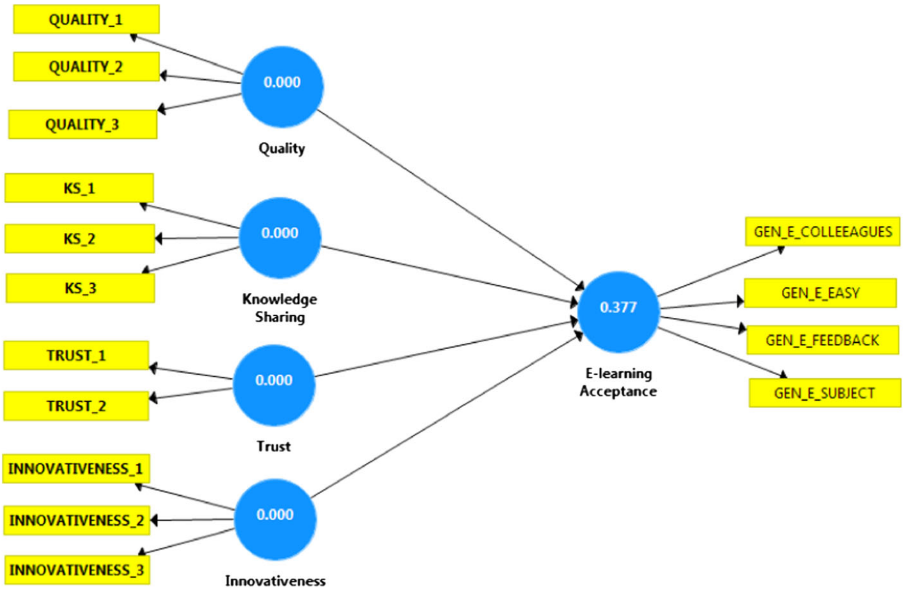

Fig. 3 Construct cross validated redundancy

at two levels, namely measurement and structural model, while concentrating on the performance of the model on the whole (Chin 2010; Henseler et al. 2012). Gof can be calculated as follows:

$$\mathrm{GoF} = \sqrt{\left(\overline{R^2} \times \overline{AVE}\right)}$$

Wetzels et al. (2009) have presented the criteria of Gof to find out if Gof, small, medium or large can be taken as global valid PLS model. These criteria are given in Table 8.

Table 9 given above shows that Gof has a value of 0.703. This shows that the Gof model of the study is large enough to show adequate global PLS model validity.

5.2.5 Hypotheses testing - path coefficient

All the hypothesized associations were examined using the structural equation modeling (see Table 10). According to (Milošević et al. 2015) the calculated values

Table 7 Construct cross validated redundancy

Variable	SSO	SSE	$Q^2 = (1 \text{ -SSE/SSO})$
E-learning Acceptance	1004.00	625.516	0.377
Innovativeness	753.000	753.000	
Knowledge Sharing	753.000	753.000	
Quality	753.000	753.000	
Trust	502.000	502.000	

Table 8 The criteria of Gof

GoF	Result
Greater than 0.36	Large
Between 0.25 to 0.36	Medium
Less than 0.1 to 0.25	Small
Less than 0.1	No fit

of fit indices, there is appropriate structural model fit to the data for the research model suggested (Tarhini et al. 2017) in this study. The Table evidently shows that all values were within the suggested range. In addition, it can also be seen that there was support for a few direct hypotheses (Ma and Yuen 2011). Knowledge sharing (ß = 0.338; $p < 0.05$) and quality (ß = 0.555; $p < 0.01$) were found to have a positive effect on E-learning acceptance, supporting H2 and H3 (Mahmodi 2017). It should be noted that students were found to be highly affected by knowledge sharing and quality by using E-learning system, while the innovativeness influence on E-learning acceptance is non-significant. is not supported H1 because $\beta = -0.005$, $t > 0.047$, $p > 0.10$. And the trust has no effect on E-learning acceptance. is not supported H4 because $\beta = -0.034$, $t > 0.304$, $p < 0.10$.

5.3 Mediator analysis

There is a mediating effect when a third variable or construct interferes with the two other related constructs. The mediator variable then seeks to explain or justify the relationship of the original two constructs. Those associations that include a series of relationships with at least one other intervening construct are known as indirect effects. Researchers should examine mediating effects by following (Preacher and Hayes 2008) and bootstrapping the sampling distribution of the indirect effect (Santos-Vijande et al. 2016), which is appropriate for simple and different mediator models Bootstrapping should be started, followed by Indirect Effects + Confidence Interval Bias Corrected.

In the mediation analysis, we investigated the direct and indirect effects of knowledge sharing, trust, and innovativeness on E-learning acceptance through quality, knowledge sharing, and trust, respectively (see Table 11 and Fig. 4). Empirical data could substantiate the positive effects illustrated in Exhibit 11. When the more complex

Table 9 Goodness of fit of the model (Gof)

Constructs	AVE
Quality	0.764
Knowledge Sharing	0.784
Trust	0.814
Innovativeness	0.793
Average	0.78875
Constructs	R2
E-learning Acceptance	0.627
Goodness of fit GoF and Predictive	0.703

Table 10 Results of structural Model - Research Hypotheses

Hypo	Relationship	Std.Beta	Std.Error	T-value	*P*-value	Decision
H1	Innovativeness → E-learning Acceptance	−0.005	0.103	0.047	0.962	Not Supported
H2	Knowledge Sharing → E-learning Acceptance	0.338	0.114	2.972	0.003	Supported**
H3	Quality → E-learning Acceptance	0.555	0.093	5.957	0.000	Supported**
H4	Trust → E-learning Acceptance	−0.034	0.111	0.304	0.761	Not Supported

Significant at $p^{**} = <0.01$, $p^{*} <0.05$

cause-effect relationship is examined. We, therefore, combine the simple and the more complex cause effect relationships models in a mediator model (Exhibit 11). In addition to M1, M2, we would need to establish hypothesis M3: The direct relationship between the knowledge sharing and E-learning acceptance (Islam 2012) (Path C) is mediated by the quality (Path A-B), and trust affects E-learning acceptance (Path C) mediated through knowledge sharing (Path A-B) and innovativeness effects E-learning acceptance (Path C) mediated through trust (Path A-B). If we use the available data to empirically estimate the model, we would obtain the estimated relationships with the expected signs. When extending the model by the quality, knowledge sharing, and trust we obtain the "true" relationship between the knowledge sharing, trust, and innovativeness with the E-learning acceptance (Yusof et al. 2012). This relationship is systematically affected by the quality, knowledge sharing, and trust, which in turn can be explained by the relationship between them and E-learning acceptance.

6 Discussion

This study sought to examine whether the proposed research model was appropriate for determining the acceptance of the E-learning system. The outcomes were supportive of the fit of the proposed research model for the E-learning acceptance (Abu-Al-Aish 2014). It is found that knowledge sharing is the most significant factor that affects E-learning system acceptance (Lu and Chiou 2010). In this study, the determinant is the same as earlier studies (Yilmaz 2016; Yuen and Ma 2004). These studies had shown that knowledge sharing helped in achieving technological acceptance. In the present times, the concept of knowledge sharing has become quite intensive, which is

Table 11 Mediation calculation -indirect effect

	IV➔ Mediator	Mediator ➔ DV	Indirect Effect	SE	t-value	p-value	Bootstrapped Confidence Interval	
	Path a	Path b					95% LL	95% UL
M1	0.683	0.555	0.379	0.119	6.015	0.000	0.146	0.612
M2	0.838	0.716	0.600	0.104	5.413	0.000	0.396	0.804
M3	0.786	0.566	0.445	0.071	6.164	0.000	0.306	0.584

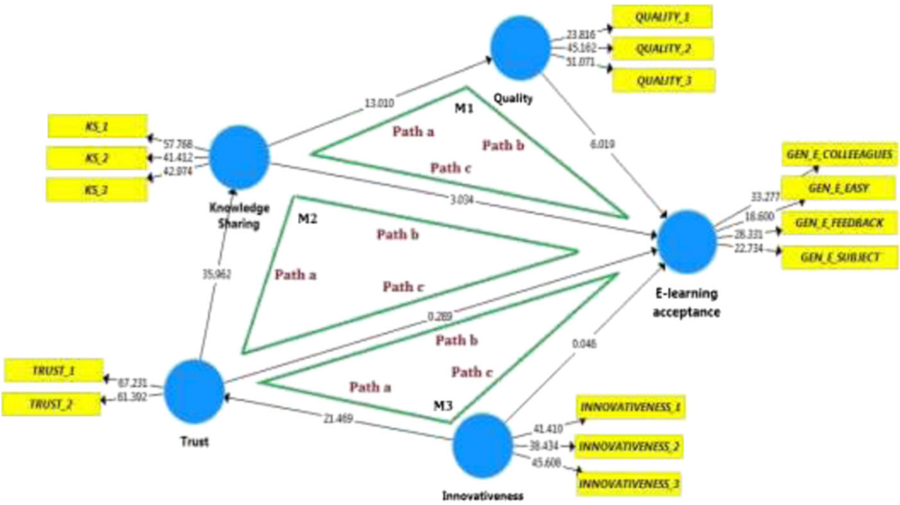

Fig. 4 Mediation calculation -indirect effect

compelling the universities to obtain extensive data and information so that they can be sustained in the E-learning system. Hence, those students who are seeking knowledge sharing will be in favor of the decision of E-learning acceptance. This will create a significant effect of knowledge sharing with respect to E-learning acceptance.

It is found that system quality influences E-learning acceptance for students. Hence, E-learning system developers should focus on the system quality factors (i.e. Accessibility, Usability, Reliability, and Stability). E-learning systems can then help in obtaining knowledge internally and externally, and offer students the potential to use present information as well as create new knowledge. This is going to play a role in making students enthusiastic about adopting E-learning technology.

There is an insignificant effect of innovativeness on the acceptance of E-learning by students. This finding is identical to the study conducted by Yatigammana et al. (2013). The data analysis showed that when postgraduate students think that it is difficult to use E-learning (complexity), then there would be a decline in the attitude and intent to use E-learning mode. When the E-learning system is not user-friendly and the users have not undergone training beforehand regarding using the computer systems, support systems, and technical knowledge, then there is a decline in adaptability and acceptance (Yatigammana et al. 2013). It was asserted by Ngafeeson and Sun (2015) that educators should try to encourage the personal innovativeness of students before implementation of the new systems. This may be possible by providing new informational and training course modules that seek to encourage students to strategically apply educational technologies while stressing on the benefits of these new technologies for students. Furthermore, the extent of exposure given to a particular technology appeared to reduce technology adoption relationships; therefore, it is important for system developers to adapt the technology to achieve the highest navigational and educational experience.

It was found that trust had a significant effect on the acceptance of E-learning. With respect to networking and distributed applications, it is important to trust a system so that another connected system or service can be used. The basis of forming a relationship between user and service providers is trusted communication. For instance, a service provider should have trust in the learner's credentials, i.e., He should be sure that the learners' credentials are not fake, and they are eligible to take part in the course or can only access a few services. According to Tarhini et al. (2016), trust is significant for describing the behavioral intention of students to adopt E-learning systems (Fong and Wang 2013; Lin et al. 2010). In fact, trust is a critical factor in the acceptance and adoption of not just E-learning systems, but also all other systems, which suggests that it is important to have better trust strategies so that the adoption of these systems occurs more rapidly.

6.1 Implications of the results

These findings can lead to various implications. It can be deduced that the proposed model can be applied to E-learning acceptance and appropriate for both the genders and all users, irrespective of their past educational achievements (Dečman 2015). Students mainly seek better performance when using E-learning systems, hence, institutions should concentrate on this. Innovativeness and trust are significant for students; however, it is found that these are not as important in the E-learning setting, keeping in view the behavioral intent for using it.

The model in this study demonstrates the essential relationships among E-learning acceptance and the four identified factors: innovativeness, quality, trust, and knowledge sharing. Analysis for the path model indicates quality and knowledge sharing have a direct effect on E-learning acceptance, relationship with knowledge sharing affect E-learning acceptance mediated through quality; trust affects E-learning acceptance mediated through knowledge sharing and innovativeness effects E-learning acceptance mediated through trust. Figure 5 presents the relationships between E-learning acceptance and the four identified factors.

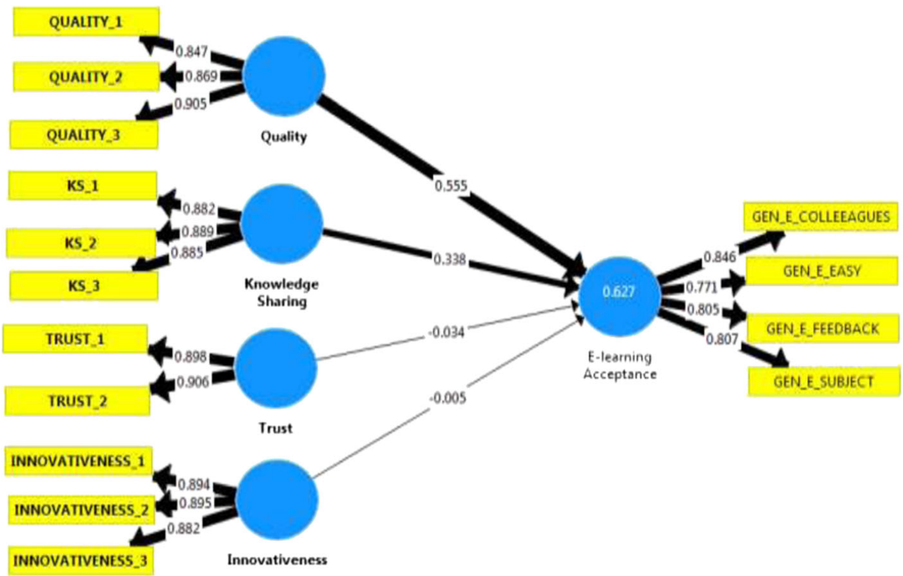

Fig. 5 The relationships among E-learning acceptance and the four identified factors

As far as the relationship between the innovativeness, quality, trust, and knowledge sharing with E-learning acceptance is concerned, the study represented that as long as the high-quality level of the knowledge sharing increased, the usage of the E-learning system will increase**.** The more there is trust in knowledge sharing, the more the usage of the E-learning system will increase.

6.2 Limitations and further research

The study has some limitations. The study was performed in two universities in the UAE to study the impact of factors on E-learning system acceptance. The study would have gained more fame had it been performed in more universities in the UAE. The factors affecting a real E-learning system can be studied through further research and by practically doing more study on the E-learning system. Furthermore, a total of just 251 students participated in the study. In future, other universities from the Arab Gulf region countries like Kuwait, Bahrain, and Qatar would be targeted. In addition, the sample size would be increased, and data collection will be done through interviews and focus groups as well. Subsequently, other studies will be carried out for assessing the attitudes of students and teachers towards E-learning.

7 Conclusion

The purpose of this article is to study the factors that affect university students' intentions to accept E-learning. This study proposes a model to identify the factors that influence the acceptance of E-learning in higher education. A structural equation model was used to analyze the data collected from 251 participants. A research model was developed. The correlation between innovativeness, knowledge sharing, trust, and quality with E-learning acceptance is examined in the basic model. Through experimental analysis of the data, the results indicated that knowledge sharing, and quality have a positive influence on the students' acceptance of E-learning systems. Innovativeness and trust were found not to be significant in affecting the E-learning system acceptance. It is observed that the E-learning systems cannot be efficient without attaining system quality. It is found in this study that system quality and knowledge sharing are the key success factors that make E-learning systems more or less efficient. Therefore, developers and designers of E-learning systems should consider the aspect of the system quality and knowledge sharing to improve the E-learning system.

References

Abbas, M., Shahid Nawaz, M., Ahmad, J., & Ashraf, M. (2017). The effect of innovation and consumer related factors on consumer resistance to innovation. *Cogent Business and Management, 4*(1), 1312058.

Abu-Al-Aish, A. (2014). *Toward mobile learning deployment in higher education* (Doctoral dissertation, Brunel University, School of Information Systems, Computing and Mathematics).

Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: an investigation in higher education. *The International Review of Research in Open and Distributed Learning, 14*(5).

Adel, R. (2017). Manage perceived e-learning quality in Egyptian context. *Total Quality Management and Business Excellence, 28*(5), 600–613.

Akter, S., D'Ambra, J., & Ray, P. (2011). An evaluation of PLS based complex models: The roles of power analysis, predictive relevance and GoF index.

Al Emran, M., & Shaalan, K. (2014a). A survey of intelligent language tutoring systems. In *Advances in Computing, Communications and Informatics (ICACCI, 2014 International Conference on* (pp. 393-399). IEEE.

Al Emran, M., & Shaalan, K. F. (2014b). E-podium technology: A medium of managing knowledge at Al Buraimi University college via M-learning. In *BCS International IT Conference*.

Al-Emran, M., & Malik, S. I. (2016). The impact of google apps at work: higher educational perspective. *International Journal of Interactive Mobile Technologies (iJIM), 10*(4), 85–88.

Al-Emran, M., & Salloum, S. A. (2017). Students' attitudes towards the use of mobile technologies in e-evaluation. *International Journal of Interactive Mobile Technologies (iJIM), 11*(5), 195–202.

Al-Emran, M., & Shaalan, K. (2015). Attitudes towards the use of mobile learning: a case study from the gulf region. *International Journal of Interactive Mobile Technologies (iJIM), 9*(3), 75–78.

Al-Emran, M., & Shaalan, K. (2017). Academics' awareness towards mobile learning in Oman. *International Journal of Computing and Digital Systems, 6*(1).

Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. *Computers in Human Behavior, 56*, 93–102.

Alkandari, B. (2015). *An investigation of the factors affecting students' acceptance and intention to use E-learning systems at Kuwait University: Developing a technology acceptance model in E-learning environments* (Doctoral dissertation, Cardiff Metropolitan University).

Alkhalaf, S., Drew, S., & Alhussain, T. (2012). Assessing the impact of e-learning systems on learners: A survey study in the KSA. *Procedia-Social and Behavioral Sciences, 47*, 98–104.

Al-rahmi, W. M., Othman, M. S., & Yusuf, L. M. (2015). Exploring the factors that affect student satisfaction through using e-learning in Malaysian higher education institutions. *Mediterranean Journal of Social Sciences, 6*(4), 299.

Ashill, N. J., & Jobber, D. (2010). Measuring state, effect, and response uncertainty: Theoretical construct development and empirical validation. *Journal of Management, 36*(5), 1278–1308.

Bakeman, R. (2005). Recommended effect size statistics for repeated measures designs. *Behavior Research Methods, 37*(3), 379–384.

Barclay, D., Higgins, C., & Thompson, R. (1995). *The partial least squares (pls) approach to casual modeling: Personal computer adoption Ans use as an illustration*.

Behera, S. K. (2013). E-and M-learning: A comparative study. *International Journal on New Trends in Education and Their Implications, 4*(3), 65–78.

Cakir, R., & Solak, E. (2014). Exploring the factors influencing E-learning of Turkish EFL learners through TAM. *TOJET: The Turkish Online Journal of Educational Technology, 13*(3).

Calvo-Mora, A., Leal, A., & Roldán, J. L. (2005). Relationships between the EFQM model criteria: a study in Spanish universities. *Total Quality Management and Business Excellence, 16*(6), 741–770.

Campbell, C., & Ma, J. J. (2015). *Looking forward, looking back: Drawing on the past to shape the future of marketing*. In *Proceedings of the 2013 World Marketing Congress*.

Chang, W. L., & Lee, C. Y. (2013). Trust as a learning facilitator that affects students' learning performance in the Facebook community: An investigation in a business planning writing course. *Computers & Education, 62*, 320–327.

Chen, H. R., & Tseng, H. F. (2012). Factors that influence acceptance of web-based E-learning systems for the in-service education of junior high school teachers in Taiwan. *Evaluation and Program Planning, 35*(3), 398–406.

Cheng, W. Y. T., & Chen, C. C. (2015). The impact of e-learning on workplace on-the-job training. *International Journal of e-Education, e-Business, e-Management and e-Learning, 5*(4), 212.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.

Chin, W. W. (2010). How to write up and report PLS analyses. In *Handbook of partial least squares* (pp. 655–690). Berlin:Springer.

Chou, H. K., Lin, I. C., Woung, L. C., & Tsai, M. T. (2012). Engagement in e-learning opportunities: An empirical study on patient education using expectation confirmation theory. *Journal of Medical Systems, 36*(3), 1697–1706.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale: Erlbaum.

Dečman, M. (2015). Modeling the acceptance of E-learning in mandatory environments of higher education: The influence of previous education and gender. *Computers in Human Behavior, 49*, 272–281.

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9–30.
Dreheeb, A. E., Basir, N., & Fabil, N. (2016). Impact of system quality on Users' satisfaction in continuation of the use of E-learning system. *International Journal of e-Education, e-Business, e-Management and E-learning, 6*(1), 13–25.
Eid, M. I., & Al-Jabri, I. M. (2016). Social networking, knowledge sharing, and student learning: The case of university students. *Computers & Education, 99*, 14–27.
El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the unified theory of acceptance and use of technology 2 (UTAUT2). *Educational Technology Research and Development*, 1–21.
Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press.
Faqih, K. M. (2016)Which is more important in e-learning adoption, perceived value or perceived usefulness? Examining the moderating influence of perceived compatibility.
Farahat, T. (2012). Applying the technology acceptance model to online learning in the Egyptian universities. *Procedia-Social and Behavioral Sciences, 64*, 95–104.
Fong, S. K. C. J., & Wang, W. F. F. L. (2013) *Hybrid learning and continuing education.*
Fook, C. Y., Sidhu, G. K., Narasuman, S., Fong, L. L., & Rahman, S. B. A. (Eds.). (2015). 7th International conference on university learning and teaching (InCULT 2014) Proceedings: Educate to innovate. Springer.
Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, 440–452.
Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika, 61*, 101–107.
Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.
Harun, A., Liew, T. S., Kassim, A. W. M., & Sulong, R. S. (2015). Smartphone dependency and its impact on purchase behavior. *Asian Social Science, 11*(26), 196.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2012). Using partial least squares path modeling in advertising research: Basic concepts and recent issues. *Handbook of research on international advertising*, *252*.
Islam, A. N. (2012). Understanding e-learning system usage outcomes in hybrid courses. In *System Science (HICSS), 2012 45th Hawaii International Conference on* (pp. 118-127). IEEE.
Jaradat, M. I. R. M. (2014). Understanding individuals' perceptions, determinants and the moderating effects of age and gender on the adoption of mobile learning: Developing country perspective. *International Journal of Mobile Learning and Organisation, 8*(3–4), 253–275.
Joo, Y. J., Lee, H. W., & Ham, Y. (2014). Integrating user interface and personal innovativeness into the TAM for mobile learning in Cyber University. *Journal of Computing in Higher Education, 26*(2), 143–158.
Kanwal, F., & Rehman, M. (2017). Factors affecting E-learning adoption in developing countries–empirical evidence from Pakistan's higher education sector. *IEEE Access*.
Kundu, S. C., & Gahlawat, N. (2016). Ability–motivation–opportunity enhancing human resource practices and firm performance: Evidence from India. *Journal of Management & Organization*, 1–18.
Lee, Y. C. (2006). An empirical investigation into factors influencing the adoption of an E-learning system. *Online Information Review, 30*(5), 517–541.
Lee, Y. H., Hsieh, Y. C., & Chen, Y. H. (2013). An investigation of employees' use of e-learning systems: Applying the technology acceptance model. *Behaviour & Information Technology, 32*(2), 173–189.
Liao, C. H., & Huang, W. L. (2009). Community adaptability, computer and internet self-efficacy, and intention of blended e-learning. *International Journal of Society Systems Science, 1*(3), 209–226.
Lin, C. S., Tzeng, G. H., Chin, Y. C., & Chang, C. C. (2010). Recommendation sources on the intention to use e-books in academic digital libraries. *The Electronic Library, 28*(6), 844–857.
Liu, Y., & Wu, Y. (2010). A survey on trust and trustworthy E-learning system. In *Web Information Systems and Mining (WISM), 2010 International Conference on* (Vol. 1, pp. 118-122). IEEE.
Liu, I. F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C. H. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning community. *Computers & Education, 54*(2), 600–610.
Lu, H. P., & Chiou, M. J. (2010). The impact of individual differences on e-learning system satisfaction: A contingency approach. *British Journal of Educational Technology, 41*(2), 307–323.
Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems, 49*(2), 222–234.
Ma, W., & Yuen, A. (2011). 11. E-learning system acceptance and usage pattern. *Technology acceptance in education: Research and issues*, 201.
Mahmodi, M. (2017). The analysis of the factors affecting the acceptance of E-learning in higher education. *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, (In Press).

Masa'd, F. M. S. (2017). Implementation of E-training in developing country: Empirical evidence from Jordan. *International Business Research, 10*(4), 42.
Matias-Reche, F., Garcia-Morales, V. J., & Rueda-Manzanares, A. (2008). Entrepreneurial size, complexity and decentralization of decision-making in the use of temporary help workers in Spain. *The International Journal of Human Resource Management, 19*(1), 169–187.
Migdadi, M. M., Abu Zaid, M. K. S., Al-Hujran, O. S., & Aloudat, A. M. (2016). An empirical assessment of the antecedents of electronic-business implementation and the resulting organizational performance. *Internet Research, 26*(3), 661–688.
Milošević, I., Živković, D., Manasijević, D., & Nikolić, D. (2015). The effects of the intended behavior of students in the use of M-learning. *Computers in Human Behavior, 51*, 207–215.
Misra, B. M. S., Torre, A. M. A. R. C., Falcão, J. G. R. M. I., Apduhan, D. T. B. O., &Gervasi, O. (2014). Computational Science and Its Applications–ICCSA 2014.
Mtebe, J. (2014). Acceptance and use of eLearning Technologies in Higher Education in East Africa.
Ngafeeson, M. N., & Sun, J. (2015). The effects of technology innovativeness and system exposure on student acceptance of e-textbooks. *Journal of Information Technology Education: Research, 14*, 55–71.
Nunnally, J. C., & Bernstein, I. H. (1994). The theory of measurement error. *Psychometric theory*, 209–247.
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891.
Purnomo, S. H., & Lee, Y. H. (2013). E-learning adoption in the banking workplace in Indonesia: An empirical study. *Information Development, 29*(2), 138–153.
Rahman, I. A., Memon, A. H., Abdullah, N. H., & Azis, A. A. A. (2013). Application of PLS-SEM to assess the influence of construction resources on cost overrun. In *Applied Mechanics and Materials* (Vol. 284, pp. 3649-3656). Trans Tech Publications.
Robinson Jr, L. (Ed.). (2014). *Marketing Dynamism & Sustainability: Things Change, Things Stay the Same...: Proceedings of the 2012 Academy of Marketing Science (AMS) Annual Conference*. Springer.
Rodríguez-Ardura, I., & Meseguer-Artola, A. (2016). What leads people to keep on e-learning? An empirical analysis of users' experiences and their effects on continuance intention. *Interactive Learning Environments, 24*(6), 1030–1053.
Roky, H., & Al Meriouh, Y. (2015). Evaluation by users of an industrial information system (XPPS) based on the DeLone and McLean model for IS success. *Procedia Economics and Finance, 26*, 903–913.
Salloum, S. A., Al-Emran, M., Monem, A. A., & Shaalan, K. (2017). A survey of text mining in social media: Facebook and twitter perspectives. *Advances in Science Technology and Engineering Systems Journal, 2*(1), 127–133.
Santos-Vijande, M. L., López-Sánchez, J. Á., & Rudd, J. (2016). Frontline employees' collaboration in industrial service innovation: Routes of co-creation's effects on new service performance. *Journal of the Academy of Marketing Science, 44*(3), 350–337.
Senapathi, M., & Srinivasan, A. (2014). An empirical investigation of the factors affecting agile usage. In *Proceedings of the 18th international conference on evaluation and assessment in software engineering* (p. 10). ACM.
Skersys, T., Butleris, R., Nemuraite, L., & Suomi, R. (Eds.). (2011). *Building the E-World Ecosystem: 11th IFIP WG 6.11 Conference on E-Business, E-Services, and E-Society, I3E 2011, Kaunas, Lithuania, October 12-14, 2011, Revised Selected Papers* (Vol. 353). Springer.
Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the royal statistical society. Series B (Methodological)*, 111–147.
Storey, C., & Kahn, K. B. (2010). The role of knowledge management strategies and task knowledge in stimulating service innovation. *Journal of Service Research, 13*(4), 397–410.
Tarhini, A., Hone, K., & Liu, X. (2013). Factors affecting students' acceptance of E-learning environments in developing countries: A structural equation modeling approach. *International Journal of Information and Education Technology, 3*(1), 54.
Tarhini, A., Mohammed, A. B., & Maqableh, M. (2016). Modeling factors affecting Student's usage behaviour of E-learning Systems in Lebanon. *International Journal of Business and Management, 11*(2), 299.
Tarhini, A., Hone, K., Liu, X., & Tarhini, T. (2017). Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: A structural equation modeling of an extended technology acceptance model. *Interactive Learning Environments, 25*(3), 306–328.
Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*(1), 159–205.
Van Raaij, E. M., & Schepers, J. J. (2008). The acceptance and use of a virtual learning environment in China. *Computers & Education, 50*(3), 838–852.

Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (Eds.). (2010). *Handbook of partial least squares: Concepts, methods and applications*. Springer Science & Business Media.
Wang, Y. D. (2014). Building trust in E-learning. *Athens Journal of Education, 1*(1), 9–18.
Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly, 33*, 177–195.
Wu, B., & Zhang, C. (2014). Empirical study on continuance intentions towards E-learning 2.0 systems. *Behaviour & Information Technology, 33*(10), 1027–1038.
Yatigammana, M. R. K. N., Johar, M. D. G. M. D., & Gunawardhana, C. (2013). Impact of Innovations attributes on E-learning acceptance among Sri Lankan postgraduate students.
Yee-Loong Chong, A., Ooi, K. B., Bao, H., & Lin, B. (2014). Can e-business adoption be influenced by knowledge management? An empirical analysis of Malaysian SMEs. *Journal of Knowledge Management, 18*(1), 121–136.
Yilmaz, R. (2016). Knowledge sharing behaviors in E-learning community: Exploring the role of academic self-efficacy and sense of community. *Computers in Human Behavior, 63*, 373–382.
Yuen, A. H., & Ma, W. W. (2004). Knowledge sharing and teacher acceptance of web based learning system. In C. McBeath, Atkinson, D. Jonas-Dwyer, and R. Phillips*, editors, Beyond the comfort zone: Proceedings of the 21st ASCILITE Conference* (pp. 975-983).
Yusof, Z. M., Ismail, M. B., Ahmad, K., & Yusof, M. M. (2012). Knowledge sharing in the public sector in Malaysia: A proposed holistic model. *Information Development, 28*(1), 43–54.

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