

E-Learning Acceptance Model (ELAM)

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ABSTRACT

This study develops an E-Learning Acceptance Model (ELAM) to investigate the relationships among the factors affecting students' acceptance of e-learning. In line with the literature, three critical success factors were used, namely instructor characteristics, information technology infrastructure, and support. ELAM was analyzed and validated using data collected from 538 university students through structural equation modeling (LISREL 8.54). The influence of the three factors on students' decision of accepting e-learning was empirically examined. The results showed that all three factors significantly and directly impacted the students' decision of accepting e-learning-based university program. Information technology infrastructure and the institution support were proven to be key determinants of the instructor characteristics as a critical success factor of e-learning acceptance by students. Implications of this work are very important for higher education institutions, researchers, and instructors.

INTRODUCTION

E-learning has become a main tool of enhancing education and training activities. Many higher education schools are integrating e-learning components into their courses in order to either offer degrees at a distance or enhance the delivery of traditional courses. E-learning can be viewed as the delivery of course content via electronic media, such as Internet, Intranets, Extranets, satellite broadcast, audio/video tape, interactive TV, and CD-ROM (Engelbrecht, 2005; Urdan & Weggen, 2000). Students use computers and telecommunications in e-learning to access online course materials via course management systems such as Blackboard (Rovai, 2002).

Many e-learning initiatives fail to achieve desired learning and teaching outcomes because of the selection of the appropriate technology, the instructor characteristics, not enough attention and support by the organization (Engelbrecht, 2005; Selim, 2004, 2006). Despite the potential of e-learning as a tool to enhance education and training, its value will not be realized if instructors, students, and organizations do not accept it as a learning tool. Students are reluctant to enroll in e-learning based courses or training programs if they are not confident that they will benefit more than traditional methods. Thus there is a need to develop a student e-learning acceptance model (ELAM).

Studying the acceptance and usage of information technologies has been the focus of many studies in the literature (Davis, 1986, 1993; Katz, 2002; Selim, 2003, 2005; Venkatesh & Davis, 2000; Ward et al., 2002). There is a large number of research articles on e-learning, however few of them address the factors contributing to its acceptance. Volery & Lord (2000) identified three factors affecting the success of online education: technology (ease of access and navigation, interface design and level of interaction); instructor (attitudes towards students, instructor technical competence and classroom interaction); and previous use of technology from a student's perspective. Soong, Chan, Chua, & Loh, (2001) identified human factors, technical competency of both instructor and student, e-learning mindset of both instructor and student, level of collaboration, and perceived information technology infrastructure as success factors of online courses. Dillon & Guawardena (1995) and Leidner & Jarvenpaa (1993) identified three main factors affect the effectiveness of e-learning environments: technology, instructor characteristics, and student characteristics. Govindasamy (2002) discussed seven e-learning quality benchmarks namely, institutional support, course development, teaching and learning, course structure, student

support, faculty support, and evaluation and assessment. Selim (2004, 2006) specified eight e-learning critical success factors that can assist universities and instructors to efficiently and effectively adopt e-learning technologies: instructor characteristics (attitude towards and control of the technology, and teaching style), student characteristics (computer competency, interactive collaboration, and e-learning course content and design), technology (ease of access and infrastructure), and support.

This study builds on the previous studies of factors identification by developing a causal structural equation model (LISREL) that includes 3 constructs (instructor characteristics, information technology, and institution support). The objective of the causal research model was to study the effects of the three factors on student e-learning acceptance which was represented as a fourth construct in the research model.

RESEARCH MODEL AND METHOD

Research Model and Hypothesis

The proposed student e-learning acceptance model (ELAM) is shown in Figure 1. As illustrated, four constructs were proposed. The instructor characteristics (INS), information technology (TECH), and organization support (SUP) were measured by five indicators. Student acceptance and usage (STD) was measured by four indicators. Students will accept e-learning if they perceive that it would help them to improve their learning effectiveness and efficiency. The INS construct assessed the e-learning related instructors' characteristics such as attitude towards e-learning and students, ability to explain the e-learning course components, and the computing skills. The information technology infrastructure construct measured on campus ease of Internet access, availability of computer labs, reliability of computer networks, and the online services. The support construct included library online services reliability, the attitude towards the technical support team, the e-learning initiative support, and the computer labs technical support.

According to the ELAM (shown in Figure 1), the instructor characteristics, the organization support, and the organization's information technology infrastructure are predicting the students' acceptance of e-learning. Accordingly, the following hypotheses were proposed:

Figure 1. ELAM research model

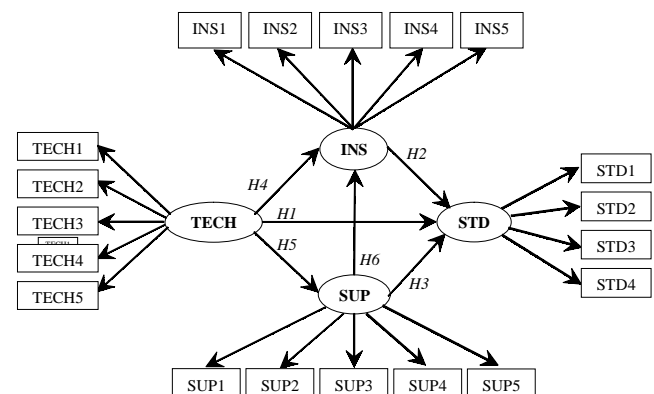


Table 1. Demographic profile of surveyed students

Item		Frequency	Percentage
Gender	Male	204	37.9
	Female	334	62.1
Age	17-19	210	39.0
	20-22	313	58.2
	23-25	12	02.2
	26-28	3	00.6
Years at UAEU	1-2	381	70.82
	3-4	153	28.44
	5-6	4	00.74
Years of e-learning	1	208	38.7
	2	197	36.6
	3	133	24.7
PC ownership	Yes	474	88.1
	No	64	11.9

- H1:** The organization's information technology will strongly affect students' acceptance of e-learning. This means that there is a positive relationship between TECH and STD.
- H2:** The instructor's characteristics will have a significant impact in determining the students' acceptance of e-learning. This postulates that there is a positive relationship between INS and STD.
- H3:** The organization's support will have a significant impact on student perception about accepting e-learning. This postulates that there is a positive relationship between SUP and STD.

The organization's information technology infrastructure affects the instructor's characteristics and the organization's support. Organization's support to e-learning initiatives affects the instructor's characteristics. Therefore the following hypotheses were proposed:

- H4:** The instructor's characteristics are affected by the organization's information technology infrastructure. Hence, there is a positive relationship between INS and TECH.
- H5:** The organization's support to e-learning is a function of the information technology infrastructure. This means that, there is a positive relationship between SUP and TECH.
- H6:** The instructor's characteristics are affected by the organization's support. This hypothesis postulates that there is a positive relationship between INS and SUP.

Participants

The courses selected for the study combine both e-learning and traditional learning tools and all of them are laptop-based courses and use active and student centered learning methods. Traditional learning tools used in the selected courses are required attendance, regular textbook, and presence of instructor during the scheduled class time. E-learning tools used are electronic student-student and student-instructor communication, asynchronous course material delivered through a Blackboard (adopted course management information system) course web, in-class active and collaborating learning activities, and student self-pacing pattern.

Data were collected through an anonymous survey instrument administered to 900 undergraduate university students during the Fall semester of 2002. Respondents for this study consisted of 538 (334 females and 204 males) – a response rate of 60% - undergraduate students enrolled in five 100-level laptop-based courses distributed over 37 class sections. All the selected courses were offered by the AACSB accredited college of Business and Economics at the United Arab Emirates University (UAEU). UAEU has 5 campuses located in 4 different geographical sites. Table 1 summarizes the demographic profile and descriptive statistics of the respondents. Student ages ranged from 17 to 28 years, with a mean age of 19.98 years (S.D. =1.256). Students came from 18 different middle eastern countries with different cultural backgrounds. They have an average GPA of 2.6 with a standard deviation of 0.54. Participants had 8 majors, namely accounting, economics, finance and banking, general business, management, management information systems, marketing,

Table 2. Reliability and descriptive statistics of ELAM's indicators

Construct	Item	Mean	S.D.	α	Extracted Variance
INS	INS1	4.00	0.99	0.91	0.68
	INS2	3.92	0.97		
	INS3	3.94	1.00		
	INS4	3.86	1.02		
	INS5	3.89	0.98		
TECH	TECH1	4.18	0.99	0.83	0.53
	TECH2	3.99	1.05		
	TECH3	3.95	0.97		
	TECH4	3.91	1.04		
	TECH5	4.13	0.91		
SUP	SUP1	4.04	0.96	0.90	0.62
	SUP2	3.86	0.94		
	SUP3	3.85	0.93		
	SUP4	3.69	1.00		
	SUP5	3.73	0.97		
STD	STD1	3.87	1.04	0.86	0.65
	STD2	3.73	0.99		
	STD3	3.86	1.15		
	STD4	3.88	1.14		

and statistics. The exposure to e-learning technologies of the participating students varied from 1 to 3 years, 38.7% had 1 year exposure, 36.6% had 2 years, and 24.7% had 3 years of exposure. All students participated voluntarily in the study.

Instrument

Indicators selected for the 4 constructs were adopted from previous research. The instrument consisted of 5 sections, a section for each construct and a demographic section. The instructor characteristics construct section included 5 indicators (INS1-INS5) which assessed the characteristics of instructors (see Appendix A for the indicator details). The five indicators were adopted from (Volery & Lord, 2000). The information technology infrastructure construct was measured by 5 indicators (TECH1-TECH5). The first indicator was adopted from (Volery & Lord, 2000) and measured the ease of Internet access at the university. The other 4 indicators were developed to capture the effectiveness of the university IT infrastructure and services. The university support construct was measured by 5 indicators (SUP1-SUP5). The 5 indicators were developed to measure the effectiveness and efficiency of the university technical support, library services, and computer labs reliability. The student acceptance was measured by 4 indicators (STD1-STD4). The first indicator was adopted from (Soong et al., 2001) to measure the student motivation to use e-learning. The second indicator used to measure the student's attitude towards active learning activities that are facilitated using e-learning and adopted from (Soong et al., 2001). The last two indicators are standard information technology usage indicators and adopted from the standard TAM instrument (Davis, 1986, 1989).

Some of the items were negatively worded. All items used a five-point Likert-type scale of potential responses: strongly agree, agree, neutral, disagree, and strongly disagree. The instrument was pre-tested by a random sample of 70 students. Minor changes to the order and wording of the items resulted from the pre-testers opinions. The survey instruments were distributed during lectures and were left to the students to be filled and returned later. Around 900 instruments were distributed, 538 usable responses were used giving a 60% response rate. The students were informed that all data were anonymous and were to be used in assessing the acceptance of e-learning technology at the university instruction environment. Table 2 shows the mean and variance of each item in the e-learning assessment instrument.

Instrument Reliability and Validity

Exploratory factor analysis (EFA) was used to detect and assess sources of variation and covariation in observed measurements (Joreskog, Sorbom, du Toit, & du Toit, 2000). The EFA was carried out using the four factors INS, TECH, SUP, and STD. Table 3 shows LISREL version

Table 3. Exploratory factor analysis for the survey instrument validity

Item	INS	TECH	SUP	STD
INS1	0.810	0.059	0.010	-0.057
INS2	0.818	-0.010	0.021	-0.022
INS3	0.858	-0.059	0.022	0.043
INS4	0.829	0.025	0.002	-0.008
INS5	0.820	0.053	0.002	0.004
TECH1	0.032	0.581	0.181	0.033
TECH2	0.035	0.728	-0.021	0.007
TECH3	0.052	0.863	-0.062	-0.040
TECH4	-0.026	0.816	0.082	-0.045
TECH5	-0.048	0.602	0.081	0.152
SUP1	-0.013	0.020	0.790	0.076
SUP2	0.108	-0.054	0.844	-0.055
SUP3	-0.001	0.088	0.721	0.130
SUP4	-0.052	0.131	0.798	-0.091
SUP5	0.010	-0.003	0.776	0.056
STD1	0.061	0.043	-0.054	0.702
STD2	0.051	-0.001	-0.026	0.754
STD3	-0.022	-0.002	0.063	0.862
STD4	-0.029	-0.016	0.040	0.900

8.54 output results for the Promax-rotated factor loadings. Items intended to measure the same construct demonstrated markedly higher factor loadings (>0.50) and are shown in bold in Table 3. This testifies to the validity of the survey instrument for further analysis.

Research instrument reliability is often estimated by Chronbach's alpha (α). Table 2 shows the α values for the four constructs of ELAM. (Hair, Anderson, Tatham, & Black, 1998) suggested that the acceptable value of α is at least 0.70. As shown in Table 2, all constructs exhibit a high degree of internal consistency as the α values of the constructs are greater than 0.80. It was concluded that the indicators could be applied for the analysis with acceptable reliability.

The average variance extracted, reflects the overall amount of variance in the indicators accounted for by the latent construct. The average variance extracted is more conservative than Chronbach's alpha (α) as a composite reliability measure and its accepted value is 0.50 or above for a construct (Fornell & Larcker, 1981). As shown in the last column of Table 2, all the extracted variances are greater than 0.50. Average variance extracted can be used to evaluate discriminant validity. The square root of average variance extracted for each construct should be greater than the correlations between that construct and all other constructs (Fornell & Larcker, 1981). Table 4 shows the correlation matrix of the constructs and the square root of average variance extracted. The discriminant validity assessment does not reveal any problems.

TESTING ELAM

As illustrated in Figure 1, ELAM is a four-factor structure. INS, TECH, and SUP constructs were measured by five indicators and STD construct was measured by four indicators. All indicators are in the reflective mode.

Figure 2. Measurement model of INS

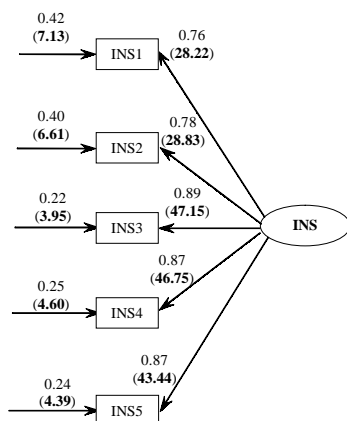


Table 4. Correlation matrix of the constructs

Construct	INS	TECH	SUP	STD
INS	0.825[*]			
TECH	0.423	0.730[*]		
SUP	0.384	0.607	0.790[*]	
STD	0.389	0.495	0.468	0.810[*]

* Square roots of the average variance extracted

As suggested by (A. H. Segars & Grover, 1993), before fitting ELAM, confirmatory factor analysis (CFA) was used to examine the four measurement models associated with the four constructs.

Testing of Measurement Models

The measurement model of INS construct is shown in Figure 2. This measurement model yielded a chi-square statistic (χ^2) of 6.33 and a p-value of 0.18, which suggested good model fit. The observed fit measures are given in Table 5 and all of them were within acceptable levels. Figure 2 shows the estimated path coefficients or standardized factor loading, as well as the associated t-values of the INS measurement model. The t-values on significant paths are shown in bold. All coefficients were significant at p value of 0.00.

The measurement model of construct TECH was examined and shown in Figure 3. A summary of the model fit measures observed for the TECH model is given in Table 5. As compared to the recommended values, all fit measures surpassed the acceptable levels suggesting a good fit. All standardized factor loadings were significant at $p=0.00$. The latent variable SUP measurement model was examined and yielded a good model fit. Figure 4 shows the estimated standardized factor loadings that were significant at $p=0.00$ and showed high validity of the measurement model. The STD measurement model is shown in Figure 5 and its fit measurements are given in Table 5 indicating good model fit. The confirmatory factor models test results confirmed the proposed 4 factors and can be used in testing ELAM with high validity and fit measures as shown in Table 5.

ELAM Structural Equation Model

ELAM research model (illustrated in Figure 1) was tested using LISREL version 8.54. The objective was to test the list of hypotheses and ELAM research model fit. ELAM model was evaluated for its validity using the asymptotic covariance matrix. The asymptotic covariance matrix and the weighted least squares method were used because all the indicator variables were ordinal (Jaakkola, 1996; Joreskog & Sorbom, 1996; Joreskog et al., 2000). The modification indices suggested by LISREL were taken into consideration and the standardized residuals were checked. A summary of the model fit measures is given in the last column of Table 5 in bold. The χ^2 statistic indicates that the model fits the data ($\chi^2 = 150.37$; $p = 0.144 > 0.05$). The ratio (χ^2 / DF) is around 1.13, which

Figure 3. Measurement model of TECH

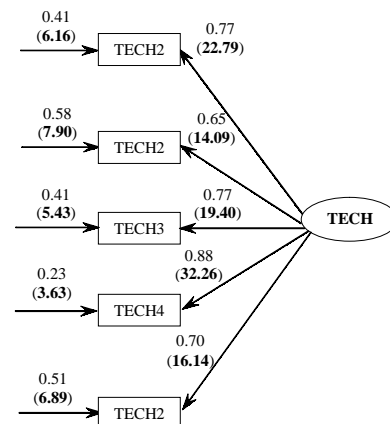


Figure 4. Measurement model of SUP

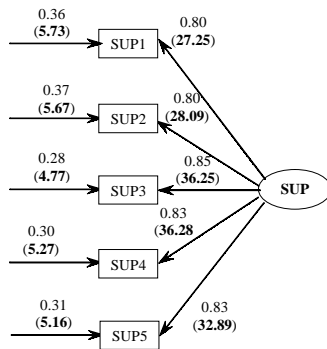


Figure 5. Measurement model of STD

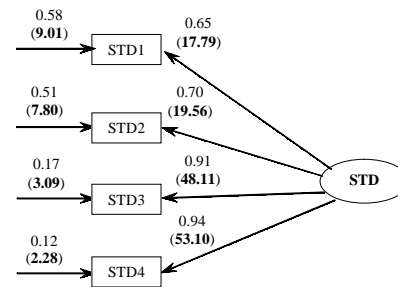


Figure 6. ELAM structural equation model

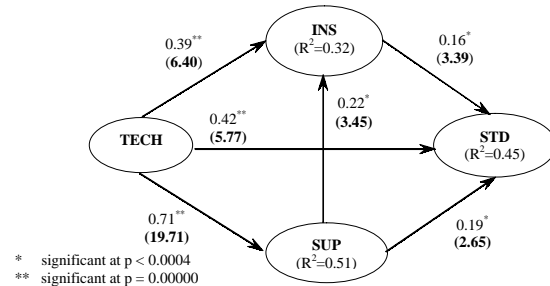


Table 5. Fit measures for INS, TECH, SUP, and STD measurement models and ELAM

Fit Measure	INS	TECH	SUP	STD	ELAM	Recommended Values
Chi-square (χ^2)	6.33	6.15	4.23	0.07	150.37	-
Degree of freedom	4	3	4	1	133	-
p-value	0.176	0.105	0.375	0.793	0.144	≥ 0.05
χ^2 /Degree of freedom (DF)	1.58	2.05	1.06	0.07	1.13	≤ 3.0
Root Mean Square Residual (RMR)	0.0169	0.0194	0.0144	0.0014	0.0934	≤ 0.10
Goodness-of-Fit Index (GFI)	0.9985	0.9982	0.9988	1.00	0.9929	≥ 0.90
Adjusted Goodness-of-Fit Index (AGFI)	0.9945	0.9912	0.9957	0.9998	0.9898	≥ 0.80
Normed Fit Index (NFI)	0.9961	0.9923	0.9957	1.00	0.9862	≥ 0.90
Nonnormed Fit Index (NNFI)	0.9964	0.9867	0.9994	1.00	0.9979	≥ 0.90
Comparative Fit Index (CFI)	0.9985	0.9960	0.9998	1.00	0.9984	≥ 0.90
Root Mean Square Error of Approximation (RMSEA)	0.0329	0.044	0.010	0.00	0.016	≤ 0.10

is below the desired value of 3.0 as recommended by the research literature (Chau, 1997; Albert H. Segars & Grover, 1998). The GFI and AGFI values are 0.9929 and 0.9898 respectively indicating a good fit. Further, RMR (0.0934), NFI (0.9862), NNFI (0.9979), CFI (0.9984), and RMSEA (0.016) are all within the acceptable levels. The estimated parameters and the corresponding t-values of the final research model appear in Table 5 and Figure 6. The results indicate that the explained variance of ELAM instructor characteristics (INS) is 0.32 and of university support (SUP) is 0.51. ELAM research model as a whole explains 0.45 of the variance in e-learning acceptance by students.

As illustrated in Figure 6 and Table 6, all the direct paths between the construct pairs are significant. The university information technology infrastructure (TECH) had a significant direct and indirect impacts on students' decision to accept e-learning (STD). As shown in Table 6, the direct effect of IT infrastructure on students' acceptance of e-learning was 65% of the total effect with a regression coefficient (β) is 0.416 and a t-value of 5.77 with $p < 0.0004$. The indirect effect of TECH on STD, which is mediated through SUP and INS, is also significant at $\beta=0.223$ with t-value of 4.33 and $p < 0.0004$. Both direct and indirect effects generated a significant total effect of 0.639 with t-value of 13.73 and $p = 0.0000$. Therefore, the hypothesis H1 is supported, which means that students' acceptance of e-learning (STD) is significantly affected by the university information technology infrastructure (TECH).

The second hypothesis H2 is also accepted because the direct path $INS \rightarrow STD$ is significant with β is 0.164 with t-value of 3.39 and $p < 0.0004$ (as indicated in Table 6 and Figure 6). This result indicated that the students' decision of accepting e-learning is positively related to the instructor's characteristics (INS). The total effect of the university support (SUP) on students' acceptance is significant at $\beta=0.223$ with t-

value of 3.12 and $p < 0.0004$ which satisfies H3. The direct effect is 84% of the total effect whereas the indirect effect contributes 16% to the total effect. This clearly shows that the e-learning acceptance is significantly dependent on the instructor's characteristics. The direct path (which represents 72% of the total effect) $TECH \rightarrow INS$ is significant since its β is 0.392, t-value of 6.40 and a p-value < 0.0004 . The indirect effect of TECH on INS, which is mediated through SUP, represented 28% of the total effect and is significant at $p < 0.0004$ as shown in Table 6. Accordingly, H4 is supported and the instructor's characteristics are highly affected by the university information technology infrastructure. The direct path $TECH \rightarrow SUP$ is significant leading to the acceptance of H5 at $p=0.0000$ (see Table 6 and Figure 6), which means that university support is significantly affected by information technology infrastructure. The direct path $SUP \rightarrow INS$ is also significant with β is 0.219, t-value of 3.45 and a p-value < 0.0004 . Therefore, hypothesis H6 is supported and the instructor's characteristics construct is highly influenced by the university support. In summary, all the direct and indirect effects on ELAM are significant leading to accepting all the 6 hypotheses.

Table 6. Direct, indirect, and total effect on constructs

Hypothesis	Path	Direct		Indirect Effect		Total Effect (t-value)	Result
		Effect (t-value)	%	Effect (t-value)	%		
H1	TECH \rightarrow STD	0.416* (5.77)	65%	0.223* (4.33)	35%	0.639** (13.73)	Accepted
H2	INS \rightarrow STD	0.164* (3.39)	100%	-	-	0.164* (3.39)	Accepted
H3	SUP \rightarrow STD	0.187* (2.65)	84%	0.036* (2.62)	16%	0.223* (3.12)	Accepted
H4	TECH \rightarrow INS	0.392* (6.40)	72%	0.156* (3.52)	28%	0.548** (13.72)	Accepted
H5	TECH \rightarrow SUP	0.711** (19.71)	100%	-	-	0.711** (19.71)	Accepted
H6	SUP \rightarrow INS	0.219* (3.45)	100%	-	-	0.219* (3.45)	Accepted

* $p < 0.0004$
 ** $p = 0.0000$

CONCLUSIONS AND DISCUSSION

Motivated by the need to utilize the several e-learning critical success factors categories available in the literature, this study is an attempt to develop a model explaining the students' decision to accept e-learning as a method of course delivery within a higher education environment. ELAM incorporated instructor's characteristics, information technology infrastructure, and support as three critical success factors affecting the decision made by students to accept e-learning. The instrument used was proved to be valid and reliable for the study. The measurement model associated with each factor was tested and proved to be valid for further analysis.

ELAM structural equation model provided good fit to the data. All path coefficients were found to be significant. The results showed that e-learning acceptance by students is highly affected by the instructor's characteristics, information technology infrastructure, and the university support to e-learning initiatives. The required instructor's characteristics included his/her attitude towards students, the technology mastering skills, and attitude toward e-learning based units in the class. The information technology infrastructure components included the student information system, online library services, university computer network reliability, computer labs availability, and the ease of on campus Internet access. The support incorporated the technical support reliability and availability, attitude towards e-learning university support, sufficiency of computers and maintenance.

ELAM explained 45% of the model's variance indicating that there are more factors to be considered. There is a need to explore more factors to increase the explained variance of ELAM.

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APPENDIX A

Student E-learning Acceptance Questions By Construct

Instructor Characteristics (INS)

- INS1 Students felt welcome in seeking advice/help
 INS 2 The instructor encourages student interaction
 INS 3 The instructor handles the E-learning units effectively
 INS 4 The instructor explains how to use the E-Learning components
 INS 5 I feel the instructor is keen that we use the E-Learning based units

Information Technology Infrastructure (TECH)

- TECH1 Easy on-campus access to the Internet
 TECH2 I can use any PC at the university using the same account and password
 TECH3 I can use the computer labs for practicing
 TECH4 I can rely on the computer network
 TECH5 I can register courses on-line using Student Information System (Banner)

E-learning Support (SUP)

- SUP1 I can access the central library website and search for materials
 SUP2 I can get technical support from technicians
 SUP3 I think that the E-Learning support is good
 SUP4 There are enough computers to use and practice
 SUP5 I can print my assignments and materials easily

Student Acceptance and Usage (STD)

- STD1 The E-Learning encourages me to search for more facts than the traditional methods.
 STD2 I learn best by construction (by participation and contribution)
 STD3 I intend to register in courses that use E-learning methods
 STD4 I like the idea of using e-learning

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