

Looking under the Bonnet: Factors Affecting Student Adoption of E-Learning Systems in Jordan

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Article abstract

The primary questions addressed in this paper are the following: what are the factors that affect students' adoption of an e-learning system and what are the relationships among these factors? This paper investigates and identifies some of the major factors affecting students' adoption of an e-learning system in a university in Jordan. E-learning adoption is approached from the information systems acceptance point of view. This suggests that a prior condition for learning effectively using e-learning systems is that students must actually use them. Thus, a greater knowledge of the factors that affect IT adoption and their interrelationships is a pre-cursor to a better understanding of student acceptance of e-learning systems. In turn, this will help and guide those who develop, implement, and deliver e-learning systems. In this study, an extended version of the Technology Acceptance Model (TAM) was developed to investigate the underlying factors that influence students' decisions to use an e-learning system. The TAM was populated using data gathered from a survey of 486 undergraduate students using the Moodle based e-learning system at the Arab Open University. The model was estimated using Structural Equation Modelling (SEM). A path model was developed to analyze the relationships between the factors to explain students' adoption of the e-learning system. Whilst findings support existing literature about prior experience affecting perceptions, they also point to surprising group effects, which may merit future exploration.

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April – 2009

Regional Focus Issue: Bridge over Troubled Waters ~ Cengiz Hakan Aydin and Yoram Eshet-Alkalai, IRRODL Regional Editors for the Middle East

Looking under the Bonnet: Factors Affecting Student Adoption of E-Learning Systems in Jordan

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Abstract

The primary questions addressed in this paper are the following: what are the factors that affect students' adoption of an e-learning system and what are the relationships among these factors?

This paper investigates and identifies some of the major factors affecting students' adoption of an e-learning system in a university in Jordan. E-learning adoption is approached from the information systems acceptance point of view. This suggests that a prior condition for learning effectively using e-learning systems is that students must actually use them. Thus, a greater knowledge of the factors that affect IT adoption and their interrelationships is a pre-cursor to a better understanding of student acceptance of e-learning systems. In turn, this will help and guide those who develop, implement, and deliver e-learning systems.

In this study, an extended version of the Technology Acceptance Model (TAM) was developed to investigate the underlying factors that influence students' decisions to use an e-learning system. The TAM was populated using data gathered from a survey of 486 undergraduate students, who were using the Moodle based e-learning system at the Arab Open University. The model was estimated using Structural Equation Modelling (SEM). A path model was developed to analyze the relationships between the factors to explain students' adoption of the e-learning system. Whilst findings support existing literature about prior experience affecting perceptions, they also point to surprising group effects, which may merit future exploration.

Keywords: E-learning; technology acceptance model; Structural Equation Modelling; system adoption; Middle East

Introduction

In educational institutions (e.g., high schools, universities, etc.) and in work life, the question of how to utilise modern information and communication technologies for learning purposes is

important. E-learning in its broadest sense refers to any learning that is electronically enabled. In a slightly narrower sense, it is learning that is enabled by the application of digital technologies. Narrowed down further, it becomes any learning that is Web-based or Internet-enabled. Instruction over the Internet is perceived by many to be a significant breakthrough in teaching and learning (Keller & Cernerud, 2002; LaRose, Gregg, & Eastin, 1998). Many higher education institutions adopt Web-based learning systems for their e-learning courses. However, there is a limited empirical examination of the factors underlying student adoption of Web-based learning systems (Ngai, Poon, & Chan, 2007). Successful implementation of a system and adoption by learners requires a solid understanding of user acceptance processes and ways of persuading students to engage with these technologies (Saadé & Bahli, 2005).

There is much research that has addressed the antecedents of technology use (Mahmood, Hall, & Swanberg, 2001) in general, but the overwhelming majority of studies have focused on users in developed countries. Whilst developing countries have much to gain from exploiting the Internet and IT in general, they have received relatively little research attention (Hasan & Ditsa, 1998). This paper's focus on Jordan not only deals with the specific experience in that country but also adds significantly to our overall knowledge of the factors underpinning student acceptance of e-learning technology.

The Arab Open University (AOU) was founded by Prince Talal bin Abdul Aziz under the umbrella of the Arab Gulf Program for United Nations Development Organizations (AGFUND) and is headquartered in Kuwait; one of its first branches was founded in Jordan in 2002. The AOU was the first Jordanian university to adopt e-learning on a widespread basis and plays a critical role in e-learning development nationally. It operates in partnership with the UK Open University (OU) and deploys a Moodle-based e-learning management system to deliver courses and support to learners.

The Technology Acceptance Model (TAM)

The TAM is an adaptation of the theory of reasoned action (Fishbein & Ajzen, 1975) specifically tailored for modelling user acceptance of information systems. Thus, the TAM is an intention-based model. According to the theory of reasoned action, beliefs influence attitudes, which lead to intentions, which then generate behaviour. The TAM adopted this belief-attitude-intention-behaviour relationship to model users' acceptance of IT (Bernadette, 1996; Di Benedetto, Calantone, & Zhang, 2003; Riemenschneider & McKinney, 2001). The TAM posits that two factors, perceived usefulness and perceived ease of use, are of primary relevance in influencing IT acceptance behaviours. Following Davis (1989), the posited relationship between perceived usefulness and perceived ease of use is that perceived usefulness mediates the effect of perceived ease of use on attitudes and intended use. In other words, while perceived usefulness has direct impacts on attitudes and intended use, perceived ease of use also influences attitude and use indirectly through perceived usefulness. These direct and indirect effects are additive. In turn, these two factors are the product of a number of variables which are exogenous to the TAM itself. Figure 1 summarises the TAM.

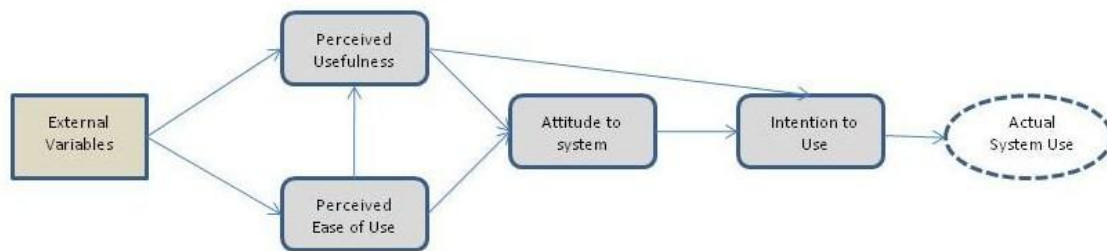


Figure 1: The Technology Acceptance Model (TAM)

Perceived ease of use is the degree to which an individual believes that learning to use a technology will require little effort. Perceived usefulness refers to the extent that a learner believes that use of the technology will improve his or her performance (see Efferson, Lalive, Richerson, Mcelreath, & Lubell, 2006).

The problem of measuring and finding the factors that determine computer usage has inspired many researchers during the past two decades. The Technology Acceptance Model (TAM) set the baseline for much future research in information and computer technology adoption and use (Davis, 1989). In the TAM, Davis proposed two determinants of computer usage: perceived usefulness and perceived ease of use. Later, other researchers expanded the TAM model to incorporate additional variables that may account for more variance in computer technology usage (see Venkatesh & Davis, 2000; Gefen & Straub, 1997). The TAM was originally developed to focus on IT system usage in the workplace. More recently, the TAM has been applied to the domain of e-learning (Carswell & Venkatesh, 2002). This paper develops an extended version of the TAM to investigate factors that influence a student's decision to use an e-learning management system.

Literature Review

Researchers have progressively developed the TAM by proposing and testing specific antecedents to its two use-belief constructs. Without considering antecedent factors, the TAM provides only very general information on users' opinions about a system and does not yield "specific information that can better guide system development" (Mathieson, 1991, p. 173). However, research on technology adoption often produces conflicting findings (Chen, Gillenson, & Sherrel, 2002) and care must be exercised in choosing potential external variables for inclusion in the study. The basis of choice proposed here is a combination of prior empirical evidence and expectations derived from the existing literature.

Subjective Norms

A subjective norm refers to a person's perception that significant others think she should or should not perform the behaviour in question (Fishbein & Ajzen, 1975). Taylor and Todd (1995) use the term "subjective norms" to refer to a person's perception of the social pressures put on him or her to perform the behaviour in question. Subjective norms have been found to have a significant direct (Ajzen, 1991; Mathieson, 1991; Taylor & Todd, 1995) and indirect (Venkatesh & Davis, 2000) effect in predicting an individual's intention to use computer technology. However, research results are variable. Some studies have found that it is not significant at all (e.g. Davis, 1986), whilst other studies have suggested that the effects of subjective norms decay over time and only remain significant in mandatory settings (Venkatesh & Davis, 2000). More recently, Lee (2006) found that subjective norms significantly influenced perceived usefulness. This study includes subjective norms as an independent variable with the expectation that they will positively influence behavioural intentions to use e-learning.

Internet Experience

Studies using the TAM have proposed that an individual's experiences with a specific technology influence perceptions of ease of use and usefulness of that technology. In addition, Kerka (1999) argued that learner success in distance learning depends on technical skills in computer operation and Internet navigation as well as the ability to cope with the substantive subject matter. Morss (1999) found empirical evidence that older students who had more experience of the technology used a learning management system (WebCT) more than younger students with less experience of IT.

System Interactivity

The key elements of learning processes are the interactions among students themselves, the interactions between faculty and students, and the collaboration in learning that results from these interactions. A major source of developments in e-learning has come via technologies that promote increased learner interaction. Interactions can be either synchronous or asynchronous. Thus, system interactivity is expected to be one of the factors that may affect students' adoption of e-learning systems. Davis, Bagozzi, and Warshaw (1989) argued that objective system characteristics have a direct impact on perceived usefulness and ease of use. In a study of the adoption of e-mail and text editors, Davis (1989) found that the TAM fully mediates the effects of system characteristics on usage behaviour.

Self-Efficacy

Self-efficacy is an important concept in social learning theory (Bandura, 1977). Self-efficacy is an individual's belief in her capability to perform certain behaviours or one's personal beliefs about her ability to perform certain tasks successfully. Several studies have found that perceptions of self-efficacy influence decisions about what behaviours to undertake, persistence in attempting certain behaviours, and the actual performance attainments of the individual with respect to those behaviours (Brown & Inouye, 1978; Wood & Bandura, 1989). In the e-learning

context, self-efficacy is interpreted as a student's self-confidence in his or her ability to perform certain learning tasks using a learning management system (LMS). A student who has a strong sense of his capability in dealing with a LMS may have a more positive perception of its ease of use and usefulness and is likely to be more willing to accept and use the system.

Technical Support

The availability of technical support is one of the important factors in determining the acceptance of technology for teaching (Williams, 2002). This is especially the case in the beginning stage of technology adoption. Venkatesh (1999) found that facilitating conditions and external control served as anchors that users employ to inform perceived ease of use about information technology. Support as a facilitating condition and external control were strong determinants of perceived ease of use. Empirical evidence shows that e-learning projects that were not successful in achieving their goals did not have access to technical advice and support (Alexander & McKenzie, 1998; Soong, Chan, Chua, & Loh, 2001). Recently, Ngai et al. (2007) extended the TAM to include technical support as an external variable in explaining use of WebCT.

Figure 2 shows our initial model. This combines the hypothesised effects drawn from the literature. Letters in brackets show the shortened names for variables that will be used in this paper.

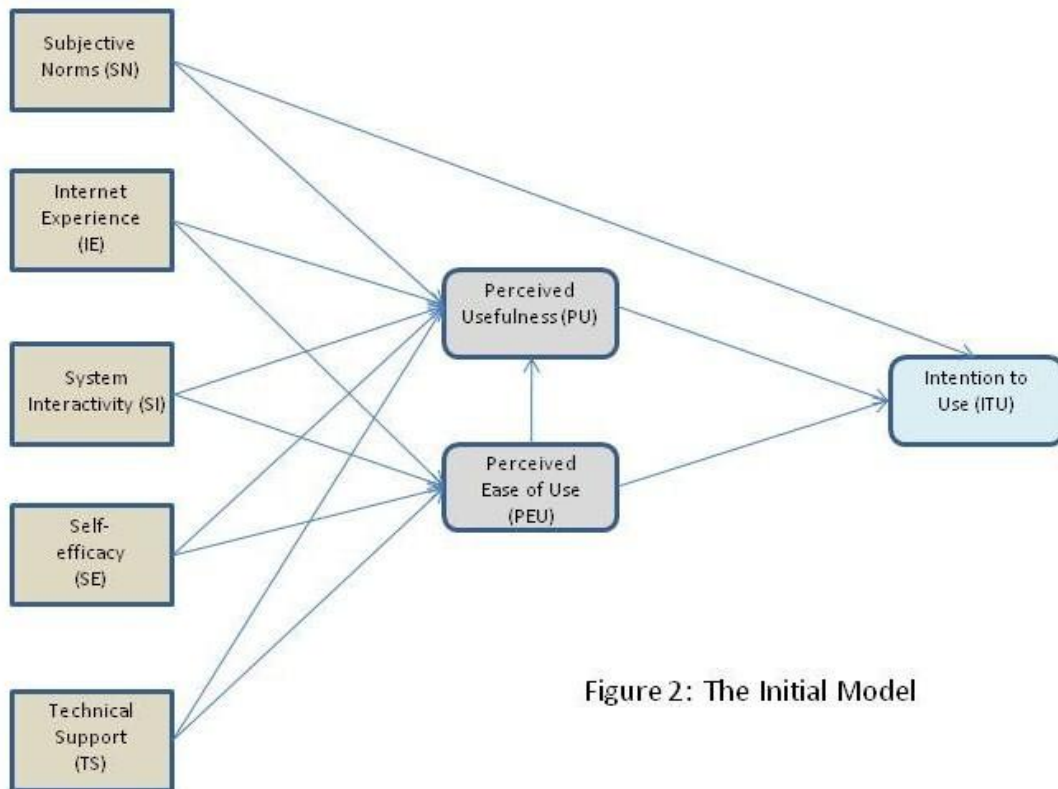


Figure 2: The Initial Model

Methodology

Participants in the Study

Participants in the study consisted of undergraduate students who were taking the last lecture of the first basic computer literacy classes at the Arab Open University (AOU) in Jordan. Participation in this study was voluntary, and 486 of 654 students (74.3%) who were enrolled in these classes agreed to take part. Sixteen questionnaires with significant levels of missing data were identified and removed from the study. Thus, 470 completed questionnaires were included in the analysis. A summary of demographic characteristics of participants is shown in Table 1.

Table 1

Summary of Demographic Characteristics of Research Participants

Variable	No. of Respondents	Percent (%)
Gender:		
Male	151	32
Female	319	68
Age:		
Under 20 years	31	6.6
20 - under 30 years	283	60.2
30 - under 40 years	133	28.3
Above 40 years	23	4.9
Faculties:		
Faculty of Language Studies	120	25.5
Faculty of Business Studies	72	15.3
Faculty of Computing Studies	60	12.8
Faculty of Educational Studies	214	45.5
Faculty of General Studies	4	0.9
Occupation:		
Not working	200	42.5
Part-time worker	54	11.5
Full-time worker	216	46
Computer at home:		
Yes	381	81
No	89	19
Internet access at home:		
Yes	210	44.7
No	260	55.3
Internet experience:		
Never	71	15.1

Less than 1 year	127	27
1 – 2 years	65	13.9
More than 2 years	207	44

The Research Instrument

A majority of studies using the TAM have relied on survey methodology for data collection. The survey method used in this study is similar to that used in previous TAM studies, thus enabling continuity and comparability with previous research. A seven-point Likert scale was used to measure students' level of agreement or disagreement with 36 items. These items were adapted and refined from previous studies (e.g., Davis, 1986; Ajzen, 1991) to make them more specifically relevant to the current research. Appendix A specifies the survey items used in the final estimation of the model. Since Arabic is the main language spoken in Jordan, the empirical study was conducted in the Arabic language. The original survey instrument was developed in English and then independently translated into Arabic by two expert bilingual speakers with a general knowledge of higher education. The two versions were compared and a final version agreed upon. The Arabic version was pilot tested using 30 Arab Open University students to ensure usability.

Research Methods

This research uses a three-stage approach. Firstly, previous studies were reviewed to help build an initial model based on the TAM approach. Secondly, a survey was constructed to provide measures of the factors identified; the measures were further developed using confirmatory factor analysis (CFA). Finally, a structural model (summarised in Figure 2) was developed and estimated using structural equation modelling (SEM) techniques. SEM is a comprehensive statistical approach to testing hypotheses about relationships among observed and latent variables (Hoyle & Panter, 1995). A major advantage of SEM is the ability to estimate a complete model incorporating both measurement and structural considerations. In SEM the measurement model shows the statistical relationship between the latent and observable (also known as measured or indicator) variables. The measurement model does not look at relationships between latent variables. Here latent variables are those shown in the boxes of Figure 2, whilst the measured variables are the sets of responses to the individual survey questions. Thus latent variables (often called factors) are not measured directly but are estimated from observed variables. Once the measurement model that best explains the relationships has been identified or "confirmed" (i.e., uses the fewest observed variables to measure the latent variables), the structural model is estimated. This estimates potential causal dependencies between the latent variables. The structural model is usually expressed as a diagram known as a path model.

SEM techniques have been widely used in measuring user acceptance of information technology (Chau, 1996; Venkatesh, Morris, Davis, & Davis, 2003). In relation to technology uptake, a number of published studies have adopted the SEM approach; examples include Moon and Kim (2001), Selim (2003), Venkatesh (1999), and Venkatesh and Davis (2000). However, it is not the

purpose of this paper to provide a full discussion of SEM techniques and a full account can be found in Bollen (1998).

Confirmatory factor analysis (CFA) was used as the first step of the two-step sequence of analysis (identifying the measurement model). Revisions to the model were made based upon the general guidelines suggested by MacCallum (1986) and Anderson and Gerbing (1988). As a general rule, modifications are made one at a time since a single change might affect other parts of the solution. CFA was conducted using AMOS 7.

In practice, several survey items are often statistically associated with (loaded on) more than one latent variable (factor). Each of these items is removed from the estimation model one at a time, and the model re-estimated. The general sequence of item deletion begins with the item having the most factors loaded. The remaining items are used in final (measurement) model estimation. Cronbach's α is usually used to assess the internal consistency of the multi-item scales.

Results

Model Estimation

Initial model estimation indicated a poor model fit. Six common model-fit measures were used to assess the model's overall goodness-of-fit: the ratio of χ^2 to degrees-of-freedom, goodness-of-fit index, adjusted goodness-of-fit index, normalized fit index, comparative fit index and root mean square error of approximation. The initial model was only acceptable on the root mean square error of approximation test. The final model was derived through the process of progressively deleting items and re-estimating the model. In terms of overall goodness-of-fit, the final model met all six of the criteria identified above. The model also met Bollen's (1998) criteria for identification. Appendix A shows the items used in the final model estimation. The α score for each of the eight factors was higher than the usually accepted threshold level of 0.7 as Table 2 shows.

Table 2

Composite Reliability

Factor	Variables	Composite Reliability α
Perceived Usefulness	PU1 PU3 PU4	0.847
Perceived Ease of Use	PEU3 PEU4 PEU6	0.874
Intention to Use	IU1	0.877

	IU2 IU3 IU4	
Subjective Norms	SN2 SN3 SN4	0.844
Internet Experiences	IE2 IE3	0.864
System Interactivity	SI1 SI2 SI3	0.846
Self-Efficacy	SE2 SE3 SE4	0.836
Technical Support	TS2 TS3	0.802

Discriminant validity is the extent to which a given statistical construct (here a latent variable) is distinct from other constructs (Hair, Black, Babin, Anderson, & Tatham, 2006). Thus, high discriminant validity provides evidence that a statistical construct is unique and captures some phenomenon that other measures do not. Discriminant validity is said to be present when cross-correlations between indicators measuring different factors are not excessively high and, therefore, correlations between the latent variables (factors) are only moderately strong (Kline, 1998). As shown in Table 3, factor correlation coefficients, ranging from 0.389 to 0.797, all indicated that the eight constructs were correlated yet distinct constructs and, therefore, provided a strong evidence of discriminant validity. Generally, a cross-factor correlation of 0.85 or higher indicates that the two factors might be measuring the same underlying constructs.

Table 3

Factor Correlations

	PEU	PU	ITU	TS	SE	SI	IE	SN
PEU	1							
PU	0.715	1						
ITU	0.797	0.791	1					
TS	0.416	0.52	0.474	1				
SE	0.727	0.64	0.691	0.452	1			
SI	0.491	0.541	0.585	0.519	0.638	1		
IE	0.598	0.441	0.516	0.438	0.6	0.477	1	
SN	0.508	0.551	0.558	0.389	0.57	0.65	0.456	1

Correlations greater than 0.3 for the sample size of 470 used in the analysis are statistically significant at the 0.01 level. An inspection of the correlation matrix reveals that all of the inter-item correlations were significant (greater than 0.3) at the 0.01 level. The correlation matrix for the survey items (as opposed to the factor correlations discussed here) is shown in Appendix C.

The Structural Model

CFA alone is limited in its ability to examine the nature of relationships between variables beyond simple correlations (Hair et al., 2006). A structural theory is a conceptual representation of the relationships between constructs. It can be expressed in terms of a structural model that represents the theory with a set of structural equations and is usually expressed in a visual form. A path analysis for the structural equation model with latent variables (see Appendix D) was performed to evaluate the hypothesized relationships that help predict students' behavioural intentions to use e-learning systems.

The commonly used measures of model fit, based on results from an analysis of the structural model, are summarized in Table 4. The results indicated an acceptable fit to the data. The model was also fully identified according to Bollen's (1998) criteria.

Table 4

SEM Statistics of Model Fit

Model goodness-fit indexes	Recommended value	Result in this study
Chi-square		504.533 *
Degrees of freedom		208
Chi-square/degree of freedom	≤ 3.0	2.426
Goodness-of-fit index	≥ 0.90	0.914
Adjusted goodness-of-fit index	≥ 0.80	0.886
Normalized fit index	≥ 0.90	0.927
Comparative fit index	≥ 0.90	0.955
Root mean square error of approximation	≤ 0.08	0.055

Note: N = 470, * p< 0.05

Table 5 shows the effects of the observed variables on the latent variables. These do not show causality in other than a statistical sense; although, of course, we have a priori reasons (discussed at the outset of this paper) to believe that causality in the wider sense is present. Direct effects are those where a change in variable x results in a change in variable y ($x \rightarrow y$). Indirect effects occur when the change in variable y contingent on a change in x operates through a third variable z ($x \rightarrow z \rightarrow y$). The total effect is the sum of the direct and indirect effects and is the correlation between the two variables. Following Cohen (1992), total effects of greater than 0.5 can be said to be of medium strength whilst those in the 0.2 to 0.5 range can be said to be small (large effects require correlations of 0.8 or more.) Effects of size greater than 0.2 are shown in bold. R^2 (the

coefficient of determination) is a measure of the proportion of the variability in a particular variable explained by the model; for example, the model explained 75% of the variability in *Intention to Use*.

Table 5

Standardized Causal Effects

Factor	Determinant	Direct Effect	Indirect Effect	Total Effect
Perceived Ease of Use (R ² = 0.580)	IE	0.233	-	0.233
	SI	0.001	-	0.001
	SE	0.567	-	0.567
	TS	0.062	-	0.062
Perceived Usefulness (R ² = 0.613)	PEU	0.495	-	0.495
	SN	0.162	-	0.162
	IE	-0.129	0.115	-0.014
	SI	0.064	0.001	0.064
	SE	0.130	0.280	0.411
	TS	0.218	0.031	0.249
Intention to Use (R ² = 0.75)	PU	0.412	-	0.412
	PEU	0.450	0.204	0.654
	SN	0.119	0.067	0.185
	IE	-	0.099	0.099
	SI	-	0.027	0.027
	SE	-	0.424	0.424
	TS	-	0.130	0.130

However the information in Table 5 is not sufficient to tell whether or not a particular path value is (statistically) significant. To test for this we need to compare the estimates of the path values with the variability in those estimates. Table 6 shows the critical ratios (t-test values) obtained by dividing the path values by their standard errors.

Table 6

Results of Path Tests

Path	Critical Ratio	Sig. Level	Comment
IE → PEU	4.199	0.001	Sig.
SI → PEU	0.019	0.985	Not Sig.
SE → PEU	7.788	0.001	Sig.
TS → PEU	1.182	0.237	Not Sig.
SN → PU	2.647	0.008	Sig.
PEU → PU	6.734	0.001	Sig.

IE → PU	-2.280	0.023	Sig.
SI → PU	0.919	0.358	Not Sig.
SE → PU	1.616	0.106	Not Sig.
TS → PU	4.096	0.001	Sig.
SN → ITU	2.742	0.006	Sig.
PEU → ITU	7.765	0.001	Sig.
PU → ITU	6.601	0.001	Sig.

The results shown in Tables 5 and 6 should be interpreted together. Note that Table 6 does not include paths with indirect-only effects. A path with a small effect can satisfy the t-test if the standard error is also very small. However, the fact remains that the effect is so small it indicates no ‘real’ effect. This occurs in three cases (SN → PU, IE → PU and SN → ITU). Similarly a path with an acceptable effect coefficient can have a large standard error and thus not be significant on a t-test. This occurs with the SE → PU path. Only paths that satisfy both tests can usefully be regarded as being statistically significant. These are shown in bold in Table 6.

Results

The final model is summarised in Figure 3. Heavier lines indicate the stronger effects; thinner lines indicate small effects. The arrows show the implied direction of causality in the relationships between factors.

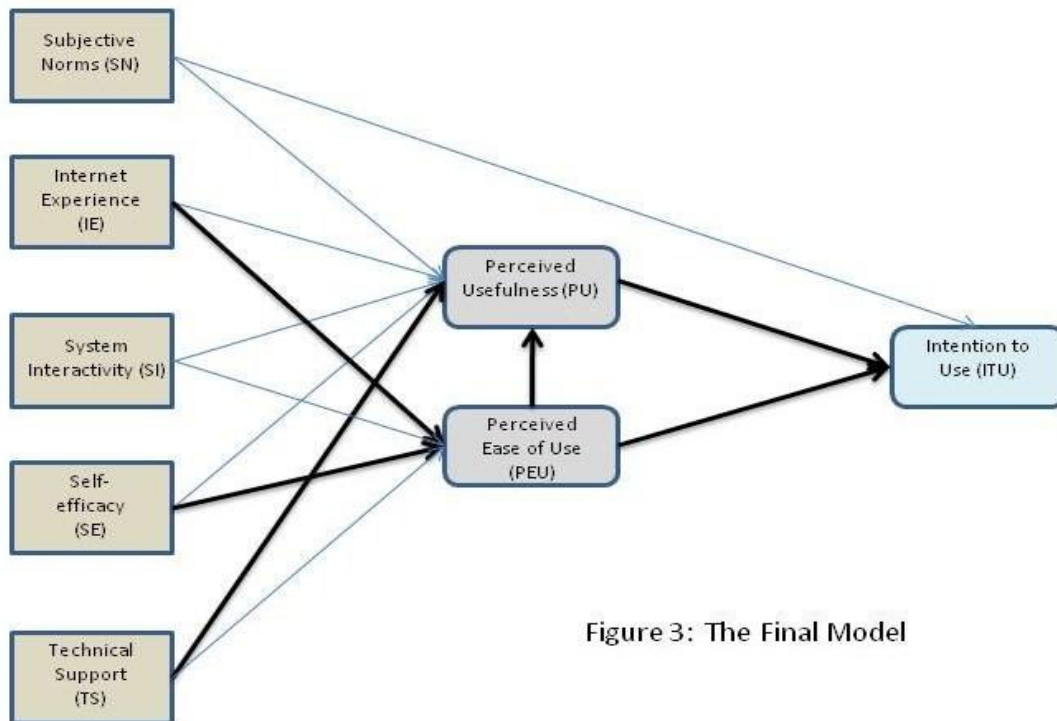


Figure 3: The Final Model

Another way of representing our results is through the estimated structural equations for the model, which are as follows:

$$\text{PU} = 0.476\text{PEU} + 0.167\text{SN} - 0.102\text{IE} + 0.146\text{SE} + 0.194\text{TS}$$
$$R^2 = 0.613$$

$$\text{PEU} = 0.191\text{IE} + 0.001\text{SI} + 0.659\text{SE} + 0.057\text{TS}$$
$$R^2 = 0.580$$

$$\text{IU} = 0.434\text{PU} + 0.456\text{PEU} + 0.129\text{SN}$$
$$R^2 = 0.75$$

The findings show that self-efficacy is an important determinant of perceived ease of use. This is consistent with the results of Venkatesh and Davis (1996). Self-efficacy showed a strong direct effect (0.567) on perceived ease of use. The result is also consistent with that of Davis (1989), who argued that computer self-efficacy and perceived ease of use are related and similar.

A student's prior Internet experience has a statistically significant influence upon perceived ease of use but not perceived usefulness. This finding is at variance with those of Igbaria, Gamers, and Davis (1995), who found that the level of computing experience had a significant direct influence on perceived usefulness and perceived ease of use.

Previous studies have demonstrated mixed results where the effects of subjective norms are concerned. Venkatesh and Davis (2000) showed a direct effect between subjective norms and both intention to use a system and perceived usefulness. Previous findings (Davis et al., 1989; Mathieson, 1991) failed to establish statistically significant relationships between these variables, as is the case here. Of course different studies refer to different times, places, technologies, and cultural contexts, and this is a potentially persuasive reason why they are not necessarily comparable.

System interactivity refers to students' perceptions of the system's ability to provide interactive communication between instructor and students and among students. This study does not provide any evidence that system interactivity affects students' adoption of e-learning systems.

Perceptions of the level of technical support available to users were found to have a direct effect on perceived usefulness and reasonable indirect effect on intention to use. This result was consistent with that of Ngai et al. (2007).

Discussion

The primary objective of this study is to analyse the factors influencing students' acceptance of e-learning. Previous findings from the field of technology acceptance research suggest that for the advantages of a technology to be attained, the technology must be accepted and used (Venkatesh

et al., 2003). The application of the TAM to e-learning is relatively new, and the power of SEM has the potential to add new insights into the factors underpinning students' acceptance of e-learning technology. The location of the study in Jordan, a developing country, is also a needed departure from the bulk of previous work.

Our results lead to four conclusions:

1. Students who are frequent and/or heavy users of the Internet are more likely to use e-learning systems.
2. Students who are confident in their ability to master an e-learning system, without help, are more likely to become users.
3. Students are reassured by the availability of back-up technical support.
4. Students believe that an e-learning system will be more useful to them if it is easy to use.

Of course we may argue that such conclusions are unsurprising and perhaps even uninspiring, but they may also point to a latent construct around the areas of confidence and path dependence from prior learning trajectories which form future areas of research, for example, de Nahlik and Morris (2008).

However the "negative" findings are also of interest. Frequent Internet users are more likely to use e-learning systems because they believe they will be easy to use rather than useful per se. This apparently contradicts the 2006 study by Efferson et al. but suggests that the payoff is of lesser importance. However, again this offers future research possibilities in that it could be explained by deconstructing perceptions of use and the nature of the payoff, to use the Efferson et al. (2006) construct. It may be that the study award is not perceived in the same way as "usefulness" but relates to perceptions of a higher order goal, which could, for example, be conceptualised by returning to Maslow (1943) and his level of "esteem" constructs.

The effects of Internet use on beliefs about LMS usefulness are an indirect product of perceptions of how easy to use a system might be. On the other hand the availability of technical support is a direct influence on perceived usefulness but not ease of use. This would seem to suggest that a well-designed e-learning system or LMS should have a reassuring and intuitive user interface, which promotes confidence among potential users.

There is no strong evidence in our work that subjective norms or system interactivity influences students' intentions to use e-learning systems. Whilst the former is of no great consequence for the design of e-learning systems, the latter would seem to run counter to our aims to develop collaborative e-learning pedagogies. The development of e-learning is in its infancy in Jordan and it may well be that students' expectations of e-learning systems did not embrace communication capabilities. Indeed the results for system interactivity and subjective norms may reinforce each other. If there is no great expectation that an e-learning system will be used for communication purposes then there will be little peer pressure to use the system.

Finally, given the subject of this special edition of IRRODL, it may also be worth considering and celebrating differences in linguistic structures and social patterns of interactions. Cultures that are more focused on oral traditions may be less engaged with e-learning (other than as a conduit to information) and may use existing social interactive structures that lie outside of any LMS to collaborate. Much e-learning material is prepared using Western pedagogic models. Are we using a less appropriate cultural lens to explore this subject?

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Appendix A

Survey Items Used in the Final Estimation of the Model

Previous Studies		Perceived usefulness
Davis, 1986	PU1	Using the e-learning system (LMS) would allow me to accomplish learning tasks more quickly
	PU3	Using the LMS would enhance my effectiveness in learning
	PU4	Using the LMS would increase my productivity in learning
		Perceived ease of use
Davis, 1986	PEU 3	My interaction with the LMS is clear and understandable
	PEU 4	Getting the information from the LMS is easy
	PEU 6	Overall, I find the LMS easy to use
		Intention to use
Davis, 1986	IU1	I intend to use the LMS to study
	IU2	I intend to study other subjects through a LMS
	IU3	I intend to increase my use of the LMS in the future
	IU4	Having used the LMS, I would recommend it to my colleagues to use it for study purposes
		Technical support
Venkatesh, 1999	TS2	A hotline is available when there is technical problem
	TS3	E-mail enquiries can be made when there is technical problem
		Internet experience
Tan and Teo, 2000	IE2	I spend many hours using the Internet
	IE3	I frequently use the Internet
		Subjective norms
Ajzen, 1991	SN2	My instructors think that I should use LMS
	SN3	People who are important to me think that I should use LMS
	SN4	People who are influence my behaviour think that I should use LMS
		System interactivity
Davis, 1989	SI1	The LMS enables interactive communications between instructor and students
	SI2	The LMS enables interactive communications among students
	SI3	The communicational tools (e-mail, chat room, forum, etc) in the LMS are effective
		Self-efficacy
Tan and Teo, 2000	SE2	I am confident of using the LMS even if there is no one around to show me how to do it

	SE3	I am confident of using the LMS even if I have never used such a system before
	SE4	I am confident of using the LMS as long as someone shows me how to do it

Appendix B

Factor Loadings

Item	Component							
	1	2	3	4	5	6	7	8
PU1	.261	.663	.191	.173	.003	.256	.143	.137
PU2	.251	.770	.065	.149	.187	.136	.125	.184
PU3	.256	.728	.179	.235	.196	.158	.158	.001
PU4	.289	.681	.179	.219	.093	.139	.102	.066
PU5	.267	.664	.366	.014	.233	.163	.055	.084
PU6	.285	.640	.398	.063	.229	.116	.086	.100
PEU1	.187	.403	.614	.086	.217	.111	.107	.189
PEU2	.304	.474	.489	.191	.151	.157	.092	.121
PEU3	.290	.238	.732	.142	.152	.145	.090	.168
PEU4	.348	.251	.620	.243	.150	.158	.117	.130
PEU5	.314	.229	.580	.356	.051	.012	.030	.316
PEU6	.327	.243	.631	.299	.091	.067	.041	.257
IU1	.592	.355	.303	.111	.092	.068	.226	.193
IU2	.628	.136	.381	.165	.081	.143	.135	.161
IU3	.664	.293	.151	.201	.188	.151	.107	.182
IU4	.614	.394	.182	.104	.188	.190	.082	.132
ATT1	.713	.275	.199	.156	.187	.126	.123	.107
ATT2	.622	.432	.147	.224	.126	.092	.163	.063
ATT3	.601	.247	.227	.313	.032	.145	.261	.038
ATT4	.692	.207	.216	.197	.201	.190	.144	.065
TS1	.234	.168	.222	.080	.270	.545	.248	-.050
TS2	.061	.204	.001	.111	.107	.782	.120	.179
TS3	.167	.198	-.009	.140	.072	.820	.094	.091
TS4	.226	.112	.344	.031	.079	.663	.202	.134
TS5	.106	.083	.359	.238	.052	.442	.440	.141
IE1	.188	.120	.262	.282	.085	.053	.245	.633
IE2	.122	.100	.212	.185	.147	.173	.092	.795
IE3	.144	.150	.156	.136	.170	.159	.129	.838
SN1	.258	.118	.130	.251	.638	.236	.119	.236
SN2	.147	.127	.214	.147	.786	.141	.091	.067
SN3	.148	.213	.107	.158	.794	.061	.206	.102
SN4	.115	.232	.026	.168	.676	.051	.372	.126
SI1	.156	.158	.091	.168	.202	.174	.782	.100
SI2	.166	.062	.024	.168	.202	.200	.789	.098
SI3	.241	.208	.099	.152	.204	.144	.670	.203
SE1	.303	.150	.278	.487	.218	.239	.330	.139
SE2	.202	.188	.275	.632	.081	.152	.213	.274

SE3	.247	.092	.250	.738	.159	.142	.150	.169
SE4	.192	.193	.089	.712	.187	.058	.271	.102
SE5	.193	.238	.111	.765	.283	.109	.036	.166

Note: Factor loadings in bold

Appendix C

Survey Item Cross-Correlations

	PEU3	PEU4	PEU6	PU1	PU3	PU4	IU1	IU2	IU3	IU4	TS2	TS3	SE2	SE3	SE4	SI1	SI2	SI3	IE2	IE3	SN2	SN3	SN4
PEU3	1																						
PEU4	0.708	1																					
PEU6	0.684	0.705	1																				
PU1	0.461	0.476	0.46	1																			
PU3	0.498	0.514	0.497	0.66	1																		
PU4	0.474	0.488	0.472	0.62	0.67	1																	
IU1	0.548	0.564	0.546	0.51	0.55	0.52	1																
IU2	0.515	0.531	0.513	0.48	0.52	0.49	0.65	1															
IU3	0.537	0.554	0.536	0.5	0.54	0.52	0.67	0.63	1														
IU4	0.521	0.536	0.519	0.49	0.53	0.5	0.65	0.61	0.64	1													
TS2	0.279	0.287	0.278	0.33	0.35	0.34	0.32	0.3	0.31	0.3	1												
TS3	0.286	0.295	0.285	0.34	0.36	0.35	0.33	0.31	0.32	0.31	0.67	1											
SE2	0.504	0.519	0.502	0.42	0.45	0.43	0.48	0.45	0.47	0.46	0.31	0.31	1										
SE3	0.501	0.516	0.5	0.42	0.45	0.43	0.48	0.45	0.47	0.45	0.3	0.31	0.7	1									
SE4	0.432	0.445	0.431	0.36	0.39	0.37	0.41	0.39	0.4	0.39	0.26	0.27	0.6	0.6	1								
SI1	0.334	0.344	0.333	0.35	0.37	0.36	0.4	0.37	0.39	0.38	0.34	0.35	0.44	0.44	0.38	1							
SI2	0.33	0.34	0.329	0.34	0.37	0.35	0.39	0.37	0.39	0.37	0.34	0.35	0.43	0.43	0.37	0.67	1						
SI3	0.318	0.328	0.317	0.33	0.36	0.34	0.38	0.36	0.37	0.36	0.33	0.34	0.42	0.42	0.36	0.64	0.63	1					
IE2	0.429	0.442	0.428	0.3	0.32	0.31	0.37	0.35	0.36	0.35	0.31	0.32	0.43	0.43	0.37	0.34	0.34	0.32	1				
IE3	0.435	0.448	0.433	0.3	0.33	0.31	0.38	0.35	0.37	0.36	0.31	0.32	0.44	0.44	0.38	0.34	0.34	0.33	0.76	1			
SN2	0.321	0.331	0.32	0.33	0.35	0.34	0.35	0.33	0.35	0.34	0.24	0.25	0.36	0.36	0.31	0.41	0.4	0.39	0.3	0.31	1		
SN3	0.356	0.367	0.355	0.36	0.39	0.37	0.39	0.37	0.38	0.37	0.27	0.27	0.4	0.4	0.35	0.45	0.45	0.43	0.33	0.34	0.65	1	
SN4	0.337	0.347	0.336	0.34	0.37	0.35	0.37	0.35	0.36	0.35	0.25	0.26	0.38	0.38	0.33	0.43	0.42	0.41	0.32	0.32	0.61	0.68	1

Appendix D

Structural Model

