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EXPLORING E-LEARNING ACCEPTANCE AMONG UNIVERSITY STUDENTS IN THAILAND: A NATIONAL SURVEY

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ABSTRACT

This study surveys the e-learning acceptance of university students in Thailand. One thousand nine hundred and eighty-one (1,981) participants completed the E-Learning Acceptance Measure (Teo, 2010) which measures three constructs that predict e-learning acceptance (tutor quality, perceived usefulness, and facilitating conditions). Data analysis was performed using structural equation modeling (SEM). The results of this study showed that the three constructs were significant predictors of e-learning acceptance. Further analysis with MIMIC (multiple indicators, multiple causes) modeling revealed that university students' e-learning acceptance was significantly different by age and perceived technology competence. Younger students and those who perceived themselves to be technologically more competent reported a higher level of e-learning acceptance than older students and those who perceived themselves as less competent in using technology.

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INTRODUCTION

Across the world, technology has been regarded among the key drivers to improve and reform teaching and learning in the schools (Afshari, Bakar, Luan, Samah, & Fooi, 2008; Luan, Atan, & Sabudin, 2010). Such importance accorded to technology by the governments is reflected in the major initiatives and substantial capital investments to build and maintain Information Communication Technology (ICT) infrastructures in the schools (Laohajaratsang, 2010; Moses, Khambari, & Luan, 2008). Among the technologies that have made their impact in education, the Internet is arguably the tool that has facilitated the transformation of teaching and learning in recent years. Through the networked technologies and wireless connections, teachers and students can now interact beyond the traditional classroom environment via electronic learning or e-learning. This possibility has allowed instructors to take advantage of the flexibility of online learning to meet the needs of many students across all levels of education, particularly those living in conditions which made them unable to learn in traditional settings (Dawson, 2006; Johnson, Cowie, De Lange, Falloon, Hight, & Khoo, 2011).

Background of the Study: E-learning in Thailand

In many developing countries such as Thailand, the Internet has been given a prominent role in the educational system. To meet the needs of students in schools and those who experience difficulties in accessing the traditional form of education, Thailand has focused much of their education budget on building ICT infrastructures and equipping teachers and students to be competent in the use of ICT tools for teaching and learning. Among the recent policies that supported the use of e-learning in the Thai education system was the 15-year Higher Education Plan (2008-2022) by the Office of the Commission of Higher Education. Among the major goals in this plan was for all higher education institutions to participate in the "distribution of education." A key strategy was to engage ICT to reduce the digital divide by expanding the access to formal and informal education for all students through elearnng (Commission of Higher Education, 2007).

The use of e-learning to create greater access and overcome barriers to teaching and learning has been well-documented in the literature. Among the Southeast Asian countries, e-learning has played an important role in reducing the rural-urban gap in education (Southeast Asian Ministers of Education Organization, 2010). Around the world, many educational institutions are offering courses by e-learning to harness the rapid development of the Internet technology for teaching and learning (Yee, Luan, Ayub, & Mahmud, 2009). In the case of Thailand, e-learning allows students to overcome limitations imposed by their locality by learning from instructors in remote locations, hence enhancing equity in the higher education sector (Suanpang & Petocz, 2006). Some reported examples of e-learning in Thai universities are the SIT e-learning system at the

King Mongkut's University of Technology Tonburi (KMUTT) and Thailand Cyber University project initiated by the Thailand Office of the Higher Education Commission. In both these institutions, e-learning was used extensively to support traditional face-to-face and online courses for self development and those leading to formal qualifications (e.g., Bachelor's degree).

Research on e-learning suggests that the extent to which users are willing to use e-learning in the way it was designed vary according to their expectations, beliefs, and experiences (Teo, 2010). It is important to understand technology acceptance in education because, unlike their counterparts in businesses, educational users exercise greater volition in deciding which technology to use, when, and how to use it. For example, students can decide whether to study through e-learning or not without few academic consequences. Under these conditions, it is useful to examine the personal factors that influence students' intention to use e-learning. However, research on e-learning had generally focused on the technical aspects of e-learning, while studies on the factors that affect users' acceptance to use e-learning such as user's perception and beliefs were limited (Duggan, Hess, Morgan, Kim, & Wilson, 1999).

Despite being given a prominent role in the Thai universities, research on e-learning in Thailand is scarce and little is known about the factors that influence e-learning acceptance among university students in Thailand. Among the existing studies involving Thai university students, the focus was on the comparison between online and traditional learning. For example, Suanpang and Petocz (2006) examined the efficiency and effectiveness of an online learning system at a university and reported that the online learning mode had resulted in better student performance than the traditional classes. Bhatiasevi (2011) found that the Thai students in his study had expressed willingness to use e-learning in order to achieve better grades. These students also showed greater satisfaction toward the e-learning materials. However, contrary findings about e-learning acceptance were reported by Siritongthaworn et al. (2006) in a study with four Thai universities. The instructors and students in their study cited poor availability of Internet access points, slow network communication, and a lack of software application as the causes for low instructor self confidence in teaching through e-learning and low participation rate in e-learning by students. These findings were corroborated by Saekow and Samson (2011) who found that the technical difficulties and lack of support had resulted in a failure to recognize the value of e-learning among university instructors.

Development of the Theoretical Model

From the literature, various theories and models have been proposed to study e-learning acceptance. Among these, two models have been widely used, the technology acceptance model (TAM) (Davis, 1989) and unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). To a large extent, the popularity of these models was attributed to their ability to explain users' acceptance (Teo & Wong, 2013). The technology acceptance model posits that behavioral intention to use a particular technology (e.g., e-learning) is a very important factor that predicts actual use. Behavioral intention is affected by attitude toward usage, as well as perceived usefulness and perceived ease of use. Both perceived usefulness and perceived ease of use jointly affect attitude toward usage, while perceived ease of use has a direct influence on perceived usefulness (Davis, 1989). The unified theory of acceptance and use of technology (UTAUT) was developed through a review and consolidation of the constructs of eight models that earlier research had employed to explain usage behavior (e.g., theory of reasoned action, technology acceptance model, and theory of planned behavior). From these, four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) were proposed to be direct determinants of users' acceptance of technology and that the constructs could be moderated by users' characteristics such as gender, age, and computer experience (Venkatesh et al., 2003).

In e-learning, the role of a tutor shifts from that of a knowledge transmitter to a facilitator, coach, and mentor (Teo, Wong, Thammetar, & Chattiwat, 2011). Teo (2010) found that when learners regarded their tutors to be of high quality, they would be willing to use e-learning and feel supported in their learning. Among the elements that impact on students' perception of tutor quality is the interaction between the teacher and students. For example, the course tutor may act as a trouble shooter or be relied upon to resolve hardware and software issues. Research suggests that e-learning does not take place simply because the learning portal or system is in place. Instead, it is the interaction between the teacher and students that determines the success of e-learning (Cegarra-Navarro & Rodriguez, 2012).

On the role of perceived usefulness in e-learning acceptance, Friedrich and Hron (2010) found that students were more likely to accept e-learning when they perceive it to be useful in achieving their educational and personal goals. In addition, perceived usefulness is a core construct of the Technology Acceptance Model and has been found to have a significant and direct influence on users' intention to use technology in educational settings (e.g., Teo, 2009a; Teo & Noyes, 2014; Teo & van Schaik, 2009).

Facilitating conditions are those in the environment that are perceived to support users in performing a task (e.g., participate in e-learning). They are also significant in predicting a user's attitude and intention to engage with technology (Teo, 2009b; Teo &Wong, 2013). For example, Groves and Zemel (2000) found that supports (e.g., skills training, information or materials available, and administrative support) were rated as very important factors which influenced the use of instructional technologies in teaching and e-learning (Miller & Lu, 2003). From the above discussion, Teo (2010) proposed a two-level theoretical model to explain e-learning acceptance among university students (Figure 1).

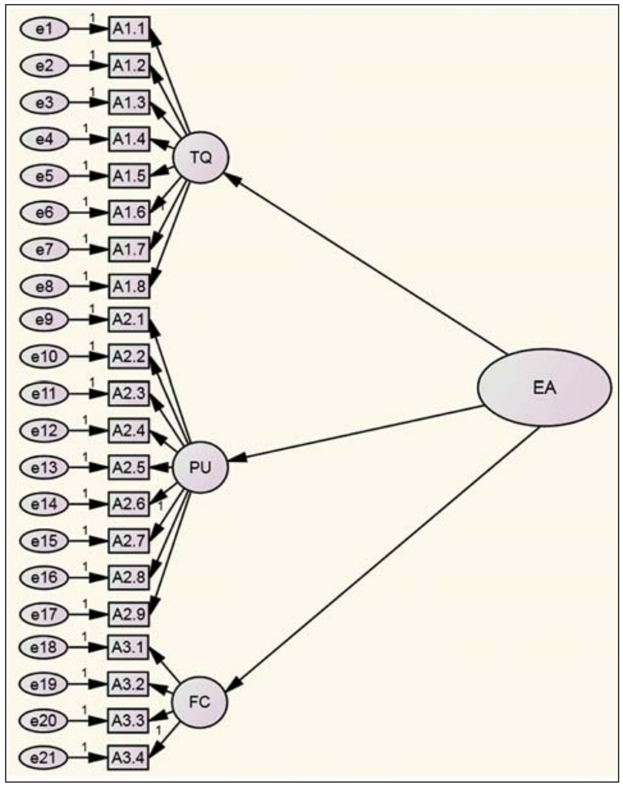

Figure 1. Theoretical model to explain university students' e-learning acceptance.
TQ = Tutor Quality; PU = Perceived Usefulness;
FC = Facilitating Conditions.

Aim of This Study

The aim of this study is twofold. First, it serves to obtain a national profile of e-learning acceptance of university students in Thailand. Second, it hopes to contribute to existing debates on e-learning acceptance by proposing a theoretical model to explain e-learning acceptance from a non-English-speaking country. In this study, e-learning is referred to as a mode of learning where students and instructor interact with each other through the Internet from different locations. Below are the guiding research questions.

1. To what extent does the theoretical model explain e-learning acceptance among university students in Thailand?

2. Are there significant differences in e-learning acceptance by students' gender, age, years of technology experience, years of internet experience, and perceived competence?

METHOD

Participants

Participants were 1981 students from seven publicly-funded universities in Thailand. Using a purposeful stratified sampling method, these universities were selected to represent all six zonal divisions used by the Office of Higher Education, Ministry of Education, Thailand. This was followed by a simple random sampling of participants within each university. By zone, participants were distributed across the North zone (33.7%), Central zone (17.5%), South zone (19.6%), East zone (12.8%), and West zone (16.4%). All participants were pre-service teachers enrolled in a teacher training program at their respective universities.

Among them, 72.9% (1444) were females and the mean age of all participants was 20.35 years (*SD* = .93). This percentage was consistent with the data gathered from the office of higher education commission in 2013, showing that pre-service teachers comprised 72% females and 28% males. The mean years of technology and Internet usage in this sample was 7.24 (*SD* = 2.50) and 3.63 (*SD* = 1.94), respectively. On a 7-point scale, with 1 representing "very low" and 7 as "very high," participants rated their perceived competence in using technology and the mean score was 5.24 (*SD* = 1.22). Table 1 shows the profile of the sample by their zonal distribution.

Procedure

Participants were invited by their lecturers during the study term and all who volunteered were briefed on the purpose of this study and informed of an option not to participate or withdraw from participating anytime during the data collection. No reward was given in monies or kind. On average, participants took about 20 minutes to complete a paper-based questionnaire.

Measure

The instrument used in this study was the 21-item e-learning acceptance measure (ElAM). Developed by Teo (2010), the ElAM was arguably the first instrument that directly measures user' acceptance of e-learning. It measures three constructs of e-learning acceptance: Tutor Quality (eight items), Perceived Usefulness (nine items), and Facilitating Conditions (four items). Developed and validated through two studies with a total sample of 386 university students in the original study, each construct in the ElAM had high internal consistency:

Table 1. Sample Distribution by Location, Gender, Age, Technology Usage, Internet Usage, and Perceived Competence

	North (n = 522)	North-East (n = 145)	Central (n = 346)	South (n = 389)	East (n = 254)	West (n = 325)
Gender						
Male	196	46	86	114	50	45
Female	326	99	260	275	204	280
Mean age (*SD*)	20.41 (.64)	20.12 (.56)	20.97 (1.12)	20.34 (.65)	19.93 (.93)	20.06 (1.15)
Mean years of technology usage (*SD*)	7.74 (2.84)	5.87 (1.53)	6.12 (1.49)	6.53 (1.25)	5.91 (1.21)	10.14 (2.48)
Mean years of Internet usage (*SD*)	3.31 (1.60)	3.43 (.99)	3.92 (2.99)	3.17 (.91)	3.36 (1.39)	4.68 (2.16)
Perceived competence* (*SD*)	5.41 (1.10)	5.37 (.87)	5.06 (1.09)	5.20 (1.02)	5.30 (.89)	5.09 (1.91)

*This variable was measured using 1 = very low and 7 = very high.

Tutor Quality (α = .99), Perceived Usefulness (α = .98), and Facilitating Conditions (α = .99). Further validation of the ElAM was performed by Teo, Wong, Thammetar, and Chattiwat (2011) in a study of 377 university students in Thailand. Using structural equation modeling, the authors obtained evidence in support of the three constructs as significant predictors of e-learning acceptance (TQ: β = .839; PU: β = 1.000; FC: β = .714). Since its development, the ElAM has been recognized as a valid tool for measuring e-learning acceptance and reported in various studies such as Chow, Herold, Choo, and Chan (2012), Bhuasiri, Xaymoungkhoun, Zo, Rho, and Ciganek (2012), and Tan (2013).

In this study, the 21 items in the ElAM were translated into the Thai language. The translation was undertaken by one of the authors in this study and her colleagues who were experienced in the use of the English and Thai languages. They held doctorates in educational technology and were familiar with the translation standard required in academic research. Measured on a 7-point Likert-type scale, with 1 = strongly disagree to 7 = strongly agree, the 21 items are shown in the Appendix.

Data Analysis

Data collected for this study were analyzed using structural equation modeling (SEM). Structural equation modeling was employed for its ability to analyze relationships between latent and observed variables. Additionally, SEM models random errors in the observed variables, thus providing more precise measurements. Other advantages of using SEM include measurement of latent variables using multiple indicators and testing hypotheses at the construct instead of item level (Hoyle, 2011). To obtain reliable results in SEM, researchers recommend the use of a large sample size (e.g., Kline, 2010). In addition, Hoelter's critical N, which refers to the sample size for which one would accept the hypothesis that the proposed theoretical model is correct at the .05 level of significance, was examined. The Hoelter's critical N for the model in this study is 822 and, given that the sample size of this study is 1981, it is adequate for the purpose of structural equation modeling.

RESULTS

Descriptive Statistics

The mean values of all items were between 5.00 and 6.00, with standard deviations less than 1.00. The skewness and kurtosis indices ranged from –1.44 to –0.80 and 1.26 to 4.58, respectively. Following Kline's (2010) recommendations, the skewness and kurtosis in the distribution of the data was considered as univariate normal. According to Teo (2010), the total possible score for ElAM ranges from 21 to 147, with scores leaning toward 147 indicating higher level of e-learning acceptance. The mean score for this study sample was 114.05, suggesting a high level of e-learning acceptance.

Evaluation of the Measurement Model

The measurement model was assessed using confirmatory factor analysis (CFA) with AMOS 7.0 and estimated using the maximum likelihood estimation (MLE) procedure. Because the MLE procedure assumes multivariate normality of the observed variables, the data in this study were examined using the Mardia's normalized multivariate kurtosis value. The Mardia's coefficient (Mardia, 1970) for the sample data was 165.63, which is lower than the value of 483 computed based on the formula $p(p + 2)$, where p equals the number of observed variables in the model (Raykov & Marcoulides, 2008). As such, multivariate normality of the sample data was assumed. Table 2 shows the results of the CFA. All parameter estimates were significant at the $p < 0.05$ level, as indicated by the t-value (greater than 1.96). The standardized estimates ranged from .40 to .59, and these were regarded as acceptable (Hair, Black, Babin, & Anderson, 2010). All constructs possessed acceptable alphas (George & Mallery, 2003) and the fit of the measurement model was acceptable (χ^2 = 514.651; χ^2/df = 2.78; TLI = 0.964; CFI = 0.968; RMSEA = 0.030; SRMR = 0.024). The adequacy of

Table 2. Results of the Measurement Model

Item	Estimate	*t*-Value	SE	Cronbach alpha
TQ1	.752	16.799	.45	.74
TQ2	.699	15.325	.40	
TQ3	1.052	21.101	.61	
TQ4	.810	17.663	.48	
TQ5	.912	18.443	.51	
TQ6	.983	19.840	.56	
TQ7	1.000	—	.55	
TQ8	.912	20.192	.57	
PU1	.992	16.916	.45	.79
PU2	1.285	20.518	.59	
PU3	.962	18.584	.51	
PU4	1.145	20.390	.59	
PU5	1.157	20.342	.59	
PU6	1.119	19.235	.54	
PU7	1.000	—	.54	
PU8	.973	19.217	.54	
PU9	.930	18.676	.52	
FC1	.980	21.249	.57	.65
FC2	1.009	20.478	.55	
FC3	1.079	20.693	.55	
FC4	1.000	—	.59	

Notes: TQ = Tutor's Quality; PU = Perceived Usefulness; FC = Facilitating Conditions; SE = Standardized Estimates.

*Indicates an acceptable level of reliability or validity.

—This value was fixed at 1.00 for model identification purposes.

the measurement model suggested that all items were reliable indicators of the hypothesized constructs they were purported to measure. A test of the theoretical model (Figure 1) revealed a good fit as well (χ^2 = 514.651; χ^2/df = 2.77; TLI = 0.964; CFI = 0.968; RMSEA = 0.030; SRMR = 0.024) and that all three constructs significantly explain e-learning acceptance (TQ: β = .99; PU: β = 1.00; FC: β = 1.00).

MIMIC Modeling

To assess if significant differences of e-learning acceptance exist by users' gender, age, years of technology use, years of Internet use, and perceived technology competence, a MIMIC (multiple indicators, multiple causes) modeling was used. This method allows the measurement of observed variables that are manifestations of an underlying latent variable that is affected by other exogenous variables that "cause" and influence the latent variable (Joreskog & Goldberger, 1975). In this study, MIMIC modeling was employed for its advantages over the use of *t*-tests to compare groups (e.g., between male and female). First, MIMIC allows the simultaneous analysis of a latent variable model with observed indicators, and second, measurement errors are modeled and computed to facilitate more precise estimation of item reliability. The modeling process involved an estimation of two parts: the measurement part (that displays the causal link among the latent variables and the observed causes) and the structural part (which shows how the latent variables are estimated through the observed variables or indicators).

The exogenous variables in this study that are assumed to explain e-learning acceptance are gender, age, years of technology use, years of Internet use, and perceived technology competence. This part of the model can be viewed as three multiple regressions: TQ, PU, and FC on gender, age, years of technology use, years of Internet use, and perceived technology competence. All the exogenous variables would be re-coded into dichotomous variables prior to the modeling process. Hence, if gender is coded such that males are 0 and females 1, a negative coefficient for gender would indicate that females have a lower level of e-learning acceptance than males. For purpose of this study, the median acceptance score for each variable other than gender (i.e., age, years of technology use, years of Internet use, and perceived technology competence) was used and converted into 0 and 1 to represent the lower and higher thresholds respectively. Figure 2 shows the MIMIC model which represents the influence of gender, age, years of technology use, years of Internet use, and perceived technology competence (left-hand side) that are represented by arrows from these variables to the latent factor (e-learning acceptance) that is explained by TQ, PU, and SN (right-hand side).

The fit of the MIMIC model was estimated using the maximum likelihood (MLE) procedure and assessed using a number of fit indices representing the absolute, comparative, and parsimonious aspects of model fit (Hair et al., 2010). They were the χ^2, χ^2/df, Tucker-Lewis index (TLI), Comparative Fit Index (CFI), Root Mean Squared Error of Approximation (RMSEA), and Standardized Root Mean Residual (SRMR). To achieve an acceptable model fit, the χ^2/df ratio should be less or equal to 3.0 while the TLI and CFI should be equal or greater than .95. In addition, the RMSEA and SRMR should be equal or smaller than .06 and .08 respectively (Hu & Bentler, 1999). The results revealed a good model fit ($\chi^2 = 22.392$, $df = 10$, $p = .013$, $\chi^2/df = 2.24$, TLI = .991, CFI = .997, RMSEA =

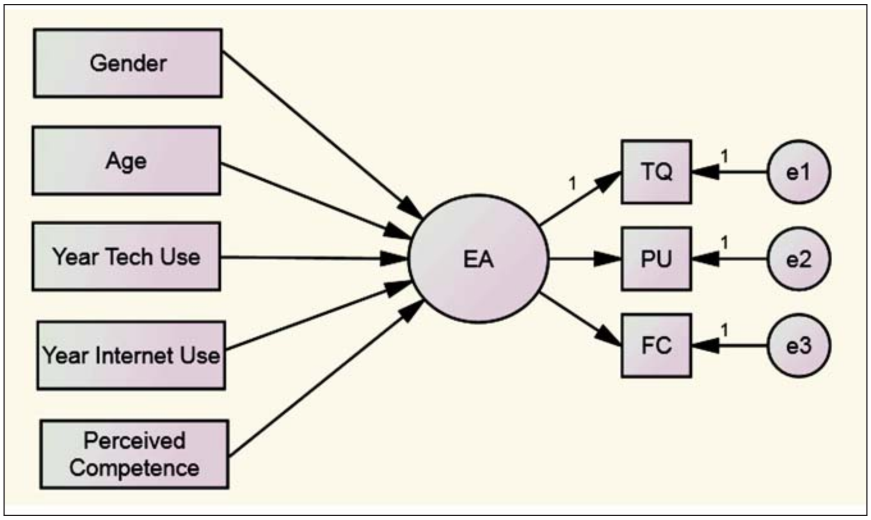

Figure 2. MIMIC model of e-learning acceptance
and its covariates.
EA = E-learning Acceptance; TQ = Tutor Quality;
PU = Perceived Usefulness; FC = Facilitating Conditions.

.025, SRMR = .009) and provided evidence to support TQ, PU, and FC as significant predictors of e-learning acceptance (β = .860, β = .908, and β = .810, respectively). In another words, TQ, PU, and FC had respectively explained 65.6%, 82.4%, and 74% of the variation in e-learning acceptance. The regression part (left side) of the model showed that there were significant differences in e-learning acceptance by age (β = –.085; $p < .01$) and perceived competence (β = .228; $p < .01$). The other three variables (gender, years of technology use, and years of Internet use) did not significantly influence e-learning acceptance. The results of the MIMIC modeling showed that younger students or those who perceived themselves to be more competent in using technology had significantly higher levels of e-learning acceptance than older students or those who perceived themselves to be less competent in using technology.

DISCUSSION

This study aims to survey the e-learning acceptance of 1981 students drawn from seven public universities across five regions in Thailand. The results revealed that participants in this study had above-average level of e-learning acceptance. Within a proposed range of 21 to 147 by Teo (2010), the mean score for the participants in this study was 114.05, approaching the maximum score of 147 in the ElAM. Such a high level of acceptance may be attributed to the drive for e-learning in education by the Thai government. It is possible that a higher e-learning acceptance was the result of visible official sanctions and endorsements at the university and national levels.

In this study, the theoretical model in which tutor quality, perceived usefulness, and facilitating conditions were posited to be significant predictors of e-learning acceptance was statistically supported. As a contribution to literature, the findings provided a first step in understanding the e-learning acceptance of a cross-section of university students in Thailand. Potentially, this study serves as a springboard for future debates and discussions on technology-mediated teaching and learning in the Asian region and the rest of the world.

From the results, there are significant differences in e-learning acceptance by age and perceived competence. In other words, younger users, or users who perceive themselves to be highly competent in using technology, accept e-learning in significantly different ways than students who are older or who perceive themselves to be less competent in using technology. These findings are consistent with current research that found younger users to have higher Internet usage than older people. Using a sample of more than 500 participants, Porter and Donthu (2006) found that age was associated with certain beliefs about the Internet and that these beliefs could mediate users' attitudes toward the use of, and ultimately, use of the Internet. This finding was shared by Wang, Wu, and Wang (2009) who found age differences on the intention to participate in mobile learning in their sample of 330 respondents from five Taiwanese organizations. They noted that there were significant differences in the perception of how easy it was to use mobile technology between the younger and older users. Age differentiation in technology acceptance is supported by research on digital natives. First introduced by Prensky (2001), digital natives were described as those who grow up with technology, are comfortable with multitasking, are reliant on graphics to communicate, and thrive on instant gratification and frequent rewards (Teo, 2013). In his discussion of digital natives, Prensky argued that age was a defining factor and that young people think and process information in fundamentally different ways compared to older people. As learners, digital natives are those who prefer to receive information fast, like to parallel-process, multi-task, and prefer their graphics before their text. They also prefer random access and function best when networked. In recent studies, researchers have called for an expanded definition of digital natives. They suggested that while age is an important factor in defining one's engagement with technology, experience with and breadth of technology use might also be significant variables for consideration (Helsper & Eynon, 2010; Li & Ranieri, 2010).

The findings of this study also revealed that students with higher perceived technology competence had significantly higher levels of e-learning acceptance. In their study with a smaller sample of Thai students, Teo, Wong, Thammetar, and Chattiwat (2011) found that perceived competence was significantly and positively correlated with e-learning acceptance but negatively correlated with age, suggesting that younger students tend to see themselves as technologically competent. They also exhibit a higher level of e-learning acceptance than their older counterparts. The implications of the above findings are that there must be a conscious effort on the part of decision-makers to create access to technology for students of all ages and level of competence in technology. In spite of the observation that younger students tend to report a higher level of perceived competence in using technology, administrators at higher institutions should ensure that students of all ages experience success at using technology for learning and personal purposes. This could range from training programs on equipping students with technology skills and widening access to computing hardware and software, to granting incentives to use technology for meeting course requirements (Teo & Koh, 2010).

Contrary to some studies, this study did not find significant differences in e-learning acceptance by gender. For example, Liaw (2002) found that female teachers expressed less interest in technology and placed lower importance on technology in the teaching and learning process compared to male teachers. On the other hand, male teachers demonstrated greater interest in technology and exhibited a higher level of confidence in their ability to use technology. However, the issue of gender in technology acceptance has been inconclusive. In recent years, there is evidence to suggest that the gender gap is fast closing due to the fact that students may have been socialized to respond to technology as an essential part of their education (Friedrich & Hron, 2010; Wong, Teo, & Russo, 2012). On the lack of significant influence of years of using technology and years of using the Internet on their e-learning acceptance, it was possible that, as a result of the widespread use of and official sanctions for e-learning, these variables had less influence in predicting students' engagement with e-learning than other variables. For example, Lin, Lin, and Laffey (2008) found that higher levels in each of social ability, learning goal orientation, perceived task value, and self-efficacy were determinants in the motivation among online learners.

Suggestions for Future Research

In the translation of the items from English to Thai, some meanings may have been lost. In this situation, more measurement errors could have been introduced into the data thus lowering the reliability of items. Future research should include a measurement invariance study to ensure that language translation does not significantly affect data quality. Although the theoretical model is statistically well fitting to the data in this study, it is possible that, in the pursuit of parsimony, Teo (2010) has excluded other variables that may impact on e-learning. Future research could consider other variables for inclusion into the theoretical model with a view to obtain greater explanatory power. Some variables may be adapted from models and theories from studies in technology acceptance

(Luan & Teo, 2009; Teo & Lee, 2010; Teo & van Schaik, 2009). Finally, the participants in this study were mostly full-time university students, and it was possible that their perception of e-learning may be different from students studying from remote locations. Future research should include participants from remote locations as they may exhibit a higher level of acceptance due to their strong needs for e-learning. Findings from comparing the e-learning acceptance of on-location students and those studying from remote locations may inform policy makers and educators on ways to achieve greater efficiency in planning and allocating resources for teaching and learning.

CONCLUSION

E-learning is among the most prolific pedagogies in modern educational practices with a high potential to impact and transform teaching and learning, especially in situations where students are constrained by their locations and social needs. Thailand is one of the largest developing countries in Asia and it is possible that other countries in the region and around the world may be confronted with similar issues and challenges in their higher education sectors. The results of this study suggest that younger students and those who reported a higher level of competence in using technology had a higher level of e-learning acceptance than the older students and those students who reported a lower level of perceived competence in using technology. It is hoped that this study would offer some fresh insights that contribute research on e-learning acceptance by highlighting the issues that confront researchers and consumers of e-learning research.

ACKNOWLEDGMENTS

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APPENDIX

Tutor Quality (TQ)

TQ1 My tutor could explain the concepts clearly
TQ2 My tutor was knowledgeable in ICT
TQ3 I was satisfied with the answers given by my tutor
TQ4 My tutor was focused on helping me to learn
TQ5 The tutorial activities were well-manage
TQ6 My tutor was accessible when I needed to consult them
TQ7 My tutor was patient when they interacted with me
TQ8 The group sessions were well facilitated

Perceived Usefulness (PU)

Because of what I have learnt from the course . . .

PU1 I am able to apply the course contents in my work
PU2 What I had learned from the course is useful to my work
PU3 I am able to use the knowledge from the course to help my colleagues
PU4 I can contribute to my work place more
PU5 I can integrate ICT in my work creatively
PU6 I can integrate ICT in my work with minimal help
PU7 I know how to search, evaluate and select appropriate IT resources to support my work
PE8 I am able to adopt and adapt ICT resources in my work
PE9 I can manage ICT resources more effectively at my work place

Facilitating Conditions (FC)

FC1 When I need help to use the e-learning system, guidance is available to me
FC2 When I need help to use the e-learning system, specialized instruction is available to help me
FC3 When I need help to use the e-learning system, a specific person is available to provide assistance
FC4 When I need help to use the e-learning system, I know where to find it

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