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Predicting acceptance of mobile technology for aiding student-lecturer interactions: An empirical study

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The current study sets out to identify determinants affecting tertiary students' behavioural intentions to use mobile technology in lectures. The study emphasises that the reason for using mobile technology in classrooms with large numbers of students is to facilitate interactions among students and lecturers. The proposed conceptual framework has four main antecedents of behavioural intention: system perception, intrinsic motivation, system and information quality, and uncertainty avoidance. Sample data was collected from 396 tertiary students in Malaysia. Results from structural equation modelling on the sample indicated that behavioural intention was significantly influenced by system and information quality, followed by intrinsic motivation, and uncertainty avoidance. System perception was not significantly predictive of behavioural intention. The proposed framework explained 54% of the variance in behavioural intention of mobile technology use in lecture classes. The study findings are indicative of the importance of system development efforts to ensure overall quality system design. The findings further suggest that mobile technology may serve as a tool to facilitate interaction among students and lecturers in large lecture classes.

Introduction

Large classes are prevalent in higher learning institutions due to notable reasons, such as being a convenient strategy for universities with budgetary and scheduling constraints, as well as other constraints such as lack of teaching staff (Dobson-Mitchell, 2011). The negative effects of large, impersonal classes for the teaching and learning of tertiary students are well documented. Reviews of literature have unearthed sound arguments against large lecture classes, and the negative consequences for both students and educators alike, backed with empirical evidences - for instance, the difficulties faced by lecturers in meeting the academic excellence standards pertaining to students' achievements in large classes with a diversity of cultural backgrounds (Biggs, 2012). Consequently, Pollock, Hamann, and Wilson (2011) compared students' perceptions of small-group classes versus large-group classes, and their findings revealed the students' clear preference for small-group classes for conducting discussions. Furthermore, their findings revealed a more equal and balanced participation of students from different ethnic backgrounds in small-group classes. There are also evidences of the effects of large classes toward students' academic achievements. Dobson-Mitchell (2011) and Johnson (2010) provided crucial empirical evidence that by increasing the size of classes, a significant negative effect on students' grades was observed, and recommended that class sizes should be reduced to increase students' academic performances.

Using Web 2.0 tools such as Twitter to gather students' feedback (Elavsky, Mislan, & Elavsky, 2011), and Clickers - instructional technologies that enable lecturers and teachers to obtain structured or semi-structured responses from all the students - Blasco-Arcas, Buil, Hernandez-Ortega, and Sese (2013) were successful in encouraging interactions, and improving attendances and learning in large classes. Rehman, Afzal, and Kamran (2013) reported both students and lecturers concurring on the importance of active interactivity in the classrooms to aid students' understanding of the subject content. Comparative research to ascertain students' preferences for lecture sessions that encourage interactivity and traditional lecture classes by Chilwant (2012) revealed a strong preference by students for classes that encourage them to actively voice their opinions and field questions. Newer tools such as the microblog with its interactive micro-messaging feature was also shown to enhance interactions in large lecture classrooms (Ledford, Saperstein, Cafferty, McClintick, & Bernstein, 2015). Frequent interactions, coupled with concise delivery of the syllabus' learning objectives, and summaries of key points with the aid of multimedia content were deemed supportive of students' learning efforts (Roopa, Bagavd Geetha, Rani, & Chacko, 2013; Sarwar, Razzaq, & Saeed, 2014). The advent of mobile messaging apps, for instance WhatsApp and Facebook Messenger have greatly eased communication. As conventional face to face lecture classes are still an integral part of higher education, and given the constraints often faced by lecturers in classes with large number of students, such messaging apps can ease interactions between students and lecturers beyond those attainable in face to face classes.

Research objective

The present study was conducted to propose and validate a theoretical framework for predicting tertiary students' intentions to use mobile technology to interact with their lecturers. Literature on technology adoption studies of information systems, motivational, and cultural theories were reviewed to identify key constructs. The technology acceptance model's (TAM) (Davis, 1989) perceived ease of use and perceived usefulness as extrinsic motivational factors are well supported across a wide range of studies, and recent studies have also highlighted the importance of intrinsic motivators such as enjoyment and self-efficacy (Giesbers, Rienties, Tempelaar, & Gilselaers, 2013; Park, Nam, & Cha, 2012; Turel, Serenko, & Giles, 2011; Yoo, Han, & Huang, 2012). One of the key phases of the system development life cycle is system design, and systems with a high quality of functionalities were deemed pivotal towards ensuring success of information system adoption (DeLone & McLean, 2003; Detlor, Hupfer, Ruhi, Zhao, 2013; Lin & Wang, 2012). Cultural influences are gaining recognition in the field of system acceptances studies, with uncertainty avoidance (UA) from national cultural dimension theory (Hofstede, Hofstede, & Minkov, 2010) proving to be an important determinant of technology acceptances studies (Hwang & Lee, 2012; Yoo & Huang, 2011). This study's proposed framework thus extends TAM's perceived ease of use and perceived usefulness constructs, and includes enjoyment, self-efficacy, information quality, system quality, and uncertainty avoidance in the proposed theoretical framework to provide a holistic insight that incorporates not just extrinsic and intrinsic motivation factors, but also factors that represent system development and cultural influences.

Conceptual background and development of research hypotheses

Detailed reviews of each hypothesised independent and dependent variable are drawn from recent literature in order to justify the inclusion of the variables.

Technology acceptance model

The value of an information system depends upon user acceptance and use (Agarwal & Prasad, 1999). Popular technology acceptance theories originated from the field of social psychology. Both the theory of reasoned action (TRA) (Fishbein & Azjen, 1975) and the theory of planned behaviour (TPB) (Azjen, 1991) claimed behavioural intention predicts actual user behaviour. TAM also postulated that behavioural intention (BI) determines user acceptance of the system, with perceived usefulness and perceived ease of use as the antecedents of behavioural intention (Davis, 1989). Perceived usefulness is the opinion that using an information system will improve productivity (Davis, 1989), thereby focusing on the users' expected benefits. Perceived usefulness is therefore a form of extrinsic motivation, that is the idea that performing a set of actions is expected to yield positive outcomes. Davis (1989) defined perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort" (p. 320). Unlike TRA's predictors of behavioural intention, TAM's perceived ease of use is postulated to affect perceived usefulness.

Recent studies proved that both perceived usefulness and perceived ease of use remain relevant as pivotal predictors of technology acceptances in the education field. These include: Calisir, Altin Gumussoy, Byraktaroglu, and Karaali's (2014) study of web-based learning system acceptances among college students; Tarhini, Hone, and Liu (2014) study on e-learning readiness; and the effectiveness of utilising computing technology in the classrooms (Padilla-Meléndez, del Aguila-Obra, & Garrido-Moreno, 2013). Use of social media tools, for instance Facebook, Twitter, and YouTube on mobile devices eases communication and information sharing among students and with their lecturers (Hrastinski & Aghaee, 2012; Veletsianos & Navarrete, 2012). Therefore, it is hypothesised that acceptance of mobile technology for promoting interactivity in large lecture classes will be determined by perceived usefulness and perceived ease of use. The framework proposed is presented in Figure 1. The following two hypotheses are proposed:

H1: Perceived usefulness positively affects behavioural intention.
H2: Perceived ease of use positively affects behavioural intention.

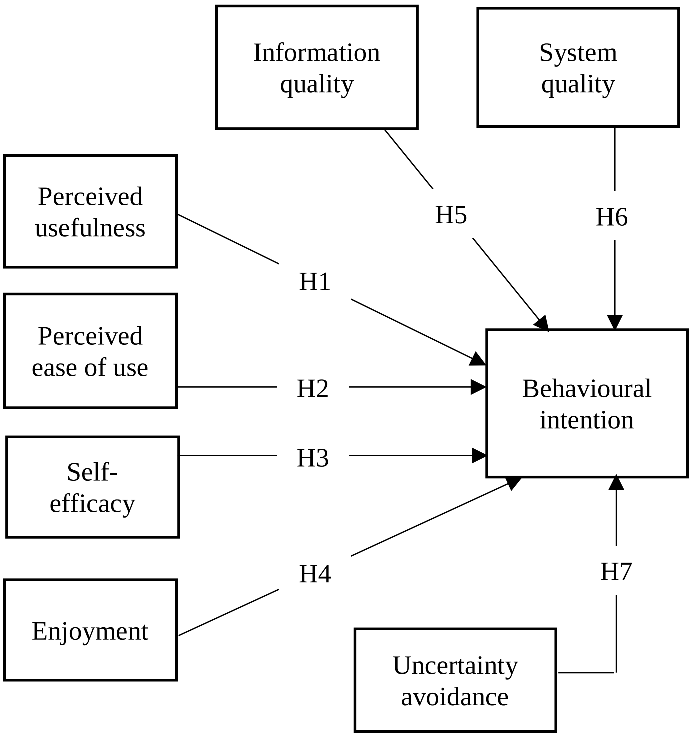

Figure 1. The proposed theoretical framework

Social cognitive theory

Social cognitive theory (SCT) is grounded in the field of cognitive psychology, the study of humans' mental processes of social interactions, problem solving, thinking, and attention or memory, and thus provides a framework for understanding and predicting user behaviour (Bandura, 1977). In studies of technology acceptances, SCT is used to explain usage behaviour by placing importance on self-efficacy as a determinant of technology acceptance. Self-efficacy reflects an individual's belief in his or her capabilities to execute a set of tasks in order to achieve specific performance goals (Bandura, 2001). In other words, self-efficacy reflects one's level of confidence. Bandura (1993) claims that low self-efficacy increases the likelihood of people avoiding tasks that are thought to be unfamiliar or difficult to perform. Compeau, Higgins, and Huff (1999) tested the influence of computer self-efficacy, outcome expectations, and anxiety on computer usage. Results gained showed self-efficacy to strongly impact users' reactions to technology.

The effects of self-efficacy on technology usage have also been explored and proven vital in many other studies, such as older studies on web-based IS acceptance (Laver, George, Ratcliffe, & Crotty, 2012; Mun & Hwang, 2003), e-service acceptance (Hsu & Chiu, 2004; Wang, Yeh, & Liao, 2013), and IS acceptance (Hasan, 2006), to recent studies relating to educators' technology acceptances (Celik & Yesilyurt, 2013; Holden & Rada, 2011), internet banking (Ariff, Yeow, Zakuan, Jusoh, & Bahari, 2012), and e-learning acceptance (Calisir et.al, 2014; Hsia, Chang, & Tseng, 2014). Lee and Lehto's (2013) study examined user behavioural intention to use YouTube for procedural learning, and findings acknowledged self-efficacy as significant predictor of usefulness towards behavioural intention. The following hypothesis is thus proposed:

H3: Self-efficacy positively affects behavioural intention.

Motivational model

In the field of motivational psychology, there are two broad forms of motivations: extrinsic and intrinsic motivations (Scott, Farh, & Podsakoff, 1988). Extrinsic motivations are driven by the expectation of external rewards after the completion of a task, such as monetary rewards, job promotions, and recognition. On the other hand, intrinsic motivations stem purely from an individual's sense of enjoyment when performing a task, without the need for external reinforcements (Scott et al., 1988; Vallerand, 1997). A growing number of studies have explored the importance of intrinsic motivational factors as significant predictors of technology acceptances, such as playfulness (Venkatesh, 2000), and enjoyment (Park, Baek, Ohm, & Chang, 2014). A recent study on e-commerce readiness among consumers posited that enjoyment was significant as a mediating predictor influencing the perceived value of online purchase (Wang et al., 2013). Particularly among students of higher education, enjoyment was identified as a factor predicting behavioural intention to use clickers for learning purposes (Wu & Gao, 2011). Teo and Noyes (2011) examined the influence of enjoyment among pre-service teachers', and their findings point to enjoyment as signification predictor of intention to use technology. A comparative study among undergraduates identified playfulness as an important predictor towards system use (Padilla-Meléndez et al, 2013). The present study thus strives to consider intrinsic motivation (conceptualised as enjoyment) as a significant determinant, and the following hypothesis is proposed:

H4: Enjoyment positively affects behavioural intention.

Delone and McLean information system (IS) success model

Delone and McLean's (2003) information system (IS) success model identified two determinants that put the focus on the information system: information quality and system quality. In this model, information quality and system quality are put forth as factors influencing system success. Information quality encompasses the effectiveness of how a system captures input and generates output, attractiveness of a system interface design, and most importantly the capability to generate relevant, useful and concise information for its user. System quality on the other hand relates to the characteristics of the whole system, such as response time, completeness of functionalities, availability and reliability of the system, ability to handle large number of user requests in a timely manner, minimal interruptions or bottlenecks, and strong security measures in place to prevent security risks.

A review of existing literature validated information and system quality as pivotal determinants. Lin and Wang (2012) study integrated the Delone and Mclean's IS success model and TAM, and findings reported both information quality and usefulness as significant predictors of e-learning acceptance. System and content quality were also identified as significant predictors of e-government services acceptance (Tan, Benbasat, & Cenfetelli, 2013). Pai and Huang (2011) also integrated the IS success model and TAM, and information quality, service quality, and system quality were mediated by perceived usefulness and ease of use to influence behavioural intention of a healthcare system. In a study to measure the acceptance of an organisation intranet, results reported that the intranet usability, design, and information quality were significant factors of behavioural intention, albeit with lower significant levels than perceived usefulness and social influence factors (Barnes & Vidgen, 2012). Therefore, the present study includes both information quality and system quality as constructs in the framework to examine its direct influence on behavioural intention.

H5: Information quality positively affects behavioural intention.
H6: System quality positively affects behavioural intention.

Uncertainty avoidance (UA)

Uncertainty avoidance encompasses the uncomfortableness and hesitation people feel due to the lack of predictability and presence of uncertainties (Hofstede et al., 2010). Uncertainty avoidance has its roots in the study of how values in organisations are influenced by cultural principles. In a comparative study between two groups of students (Americans and Koreans), the Koreans students exhibited higher level of apprehension towards adopting Web 2.0 tools (Yoo & Huang, 2011). Lower levels of uncertainty avoidance positively correlate to higher acceptance of cell phone subscription and internet use (Matusitz & Musambira, 2013).

Hwang and Lee's (2012) study to determine factors supporting consumer online purchasing decisions, found evidence to demonstrate uncertainty avoidance influencing consumer trust. Uncertainty avoidance was also found to have a moderating effect for both consumer overall perceived value and enjoyment of online purchases (Sabiote, Frías, & Castañeda, 2012). Aykut's (2009) study on e-government acceptance revealed high levels of uncertainty avoidance negatively lowers acceptance. However, another similar study in e-government acceptance reported certainty avoidance as insignificant (Lean, Zailani, Ramayah, & Fernando, 2009). Yoon (2009) explored the effects of culture on consumer adoption of e-commerce, and evidence points to uncertainty avoidance having moderate effects on the relationship between trust and intention to use. The present study theorises that low levels of uncertainty avoidance positively affect user behavioural intention. Therefore, the following hypotheses is proposed:

H7: Low levels of uncertainty avoidance positively affects behavioural intention.

Research method

The present study empirically verified the framework using an online survey written using the English language. The targeted respondents were students of higher education institutions located in urban areas in Malaysia. A 5-point Likert scale and a fixed nominal scale was used. The main questionnaire items were built based on the framework's constructs (perceived usefulness, perceived usefulness, enjoyment, self-efficacy, information quality, system quality, and uncertainty avoidance). To ensure validity of the survey instruments, a pilot test was conducted where the survey was handed to 10 selected undergraduates across multiple disciplines of study. The students completed the survey questions within 10 minutes, and feedback was gathered. This ensured that the survey items made sense and fitted the scope of the study's objectives. Most importantly, the pilot test was conducted in order to verify that students understand the technology terminologies and definitions provided, especially students of non-sciences disciplines. Based on comments gathered, several survey item wordings and phrases were refined to improve clarity.

The final survey had four main sections. The first section consisted of six questions to determine respondents' gender, age, higher learning institutions, and educational details. Respondents' anonymity was ensured as the questions did not identify the respondents' identity. The second section consisted of four questions to identify respondents' currently owned types of mobile devices, as well as their means of internet access, and whether they were using their mobile devices to support their learning activities. The third section consisted of two questions to determine whether the respondents' preferred smaller or bigger lecture classes, as well as checklist option to ascertain any interaction difficulties faced in large classes with peers and lecturers. The final section was the main section of the survey. Five item statements for each construct were presented using a 5-point Likert scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Convenience sampling was chosen for the study. Targeted respondents were students of higher learning institutions. No exclusion rules were required, and all students regardless of study discipline and levels were welcome to participate in the survey. Data collection efforts ceased when the sample size reached 398, a sufficient sample size required for statistical analyses (Hair, Black, Babin, Anderson, & Tathamal, 2006).

Data analysis

SPSS 21 and AMOS 21 for Windows were used for data analysis. Both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to refine the survey items, and to assess items' reliability, internal consistency, and identify common biases. Structural equation modelling (SEM) was then used to test the proposed hypotheses. The demographic details of the respondents are shown in Table 1. Average age of the respondents was 21 years old. Of the 396 respondents, 258 (65.2%) were undergraduates, and 131 (33.1%) respondents were from the IT discipline. In terms mobile devices usage, 373 (94.2%) of the respondents reported using their mobile devices for learning purposes. All respondents' higher learning institutions provides free Wi-Fi, with 379 (95.7%) respondents able to access the internet via Wi-Fi using their mobile devices. In terms of lecture size preferences, 281(70.9%) respondents preferred smaller classes (less than 50 students), and 89 (22.5%) respondents were neutral about lecture classes size.

Table 1
Demographic profile of respondents

	Frequency	Percentage
Gender		
Male	198	50.0
Female	198	50.0
Level of education		
Postgraduate	24	6.1
Undergraduate	258	65.2
Diploma	70	17.7
Foundation	44	11.1
Academic field		
Information technology	131	33.1
Business	100	25.3
Engineering	73	18.4
Accountancy	30	7.6
Law	28	7.1
Sciences	16	4.0
Social science	8	2.0
Humanities	3	.8
Architecture	3	.8
Language	2	.5
Education	1	.3
Mathematics	1	.3

Factor analysis

With the exception of item SE2, the skewness and kurtosis of the sample ranged from -1.255 to .024, and -.872 and 1.764 respectively. The items' skewness and kurtosis were well within the cut-off point of absolute value 3 and 10 respectively, indicating the survey were fairly normally distributed (Kline, 2005). Item SE2 had a skewness index of 12.040 and kurtosis of 203.443, well outside the acceptable range. SE2 was subsequently excluded from factor analysis.

EFA was performed to ensure stability of the constructs' research items (excluding SE2). Maximum likelihood extraction with Varimax rotation was selected. Kaiser-Meyer-Olkin value was .958, indicating sample size adequacy and above the recommended value of .6. Bartlett's test of sphericity reached statistical significance, supporting the factorability of the correlation matrix (x^2 = 14937.90, df = 741, p < 0.001). Diagonals of the anti-image correlation matrix were also all above .5; all communalities above .3. Results revealed the presence of five factors, and explained a total of 71.49% of the variance. Perceived ease of use and perceived usefulness items loaded together, and the factor named system perception (SP). Similar results were achieved for enjoyment and self-efficacy, and the factor named user intrinsic motivation (IM). Items from information quality and system quality expectedly loaded together, and named system and information quality (SIQ). One item was excluded due to cross-loading. Factor loadings of each construct's items are presented in Table 2.

Table 2
Rotated component matrix of a five factor solution

Item	Factor				
	SP	IM	SIQ	UA	BI
BI1[a]	.448	**.467**	.403	.040	.377
BI2	.251	.277	.350	.076	**.488**
BI3	.192	.238	.304	.143	**.768**
BI4	.308	.349	.333	.166	**.768**
BI5	.382	.427	.392	.106	**.659**
PU1	**.766**	.465	.220	.037	.106
PU2	**.790**	.509	.257	.045	.163
PU3	**.594**	.368	.186	.059	.259
PU4	**.741**	.543	.300	.073	.163
PU5	**.771**	.445	.182	.116	.206
PEOU1	**.799**	.514	.271	.027	.119
PEOU2	**.779**	.473	.214	.094	.166
PEOU3	**.835**	.516	.256	.024	.099
PEOU4	**.660**	.492	.274	.126	.112
PEOU5	**.820**	.599	.345	.011	.135
E1	.268	**.591**	.268	.059	.191
E2	.324	**.697**	.324	.069	.269
E3	.233	**.523**	.233	.118	.300
E4	.265	**.720**	.265	.069	.273
E5	.310	**.776**	.310	.032	.231
SE1	.373	**.731**	.373	-.034	.114
SE3	.201	**.762**	.364	.035	.170
SE4	.364	**.579**	.339	.072	.226
SE5	.339	**.719**	.425	.081	.166
IQ1	.425	.259	**.672**	.131	.179
IQ2	.431	.188	**.703**	.039	.173
IQ3	.293	.390	**.773**	.068	.166
IQ4	.391	.510	**.816**	.040	.158
IQ5	.460	.536	**.666**	.033	.156
SQ1	.229	.384	**.464**	.123	.207
SQ2	.154	.469	**.552**	.122	.202
SQ3	.323	.325	**.598**	.043	.303
SQ4	.465	.445	**.541**	-.015	.291
SQ5	.498	.488	**.509**	-.014	.242
UA1	.036	.034	.054	**.784**	.079
UA2	.023	.033	.027	**.837**	.044
UA3	.057	.052	.114	**.859**	.072
UA4	.095	.096	.076	**.864**	.077
UA5	.074	.083	.082	**.910**	.074

Note: Major loading for each item is in bold. SP = system perception; IM = intrinsic motivation; SIQ = system and information quality; UA = uncertainty avoidance; BI = behavioural intention
[a] BI1 was excluded from further analysis

The Cronbach alpha coefficients were SP (system perception) .955, IM (intrinsic motivation) .909, SIQ (system and information quality) .932, UA (uncertainty avoidance) .934, and BI (behavioural intention) .884, all exceeding the recommended cut-off value of .7 (Nunnally & Bernstein, 1994). Thus, acceptable internal consistencies were met. The framework was then updated (Figure 2). The final hypotheses are:

H1: System perception positively affects behavioural intention.
H2: Intrinsic motivation affects behavioural intention
H3: System and information quality positively affects behavioural intention.
H4: Low levels of uncertainty avoidance positively affects behavioural intention.

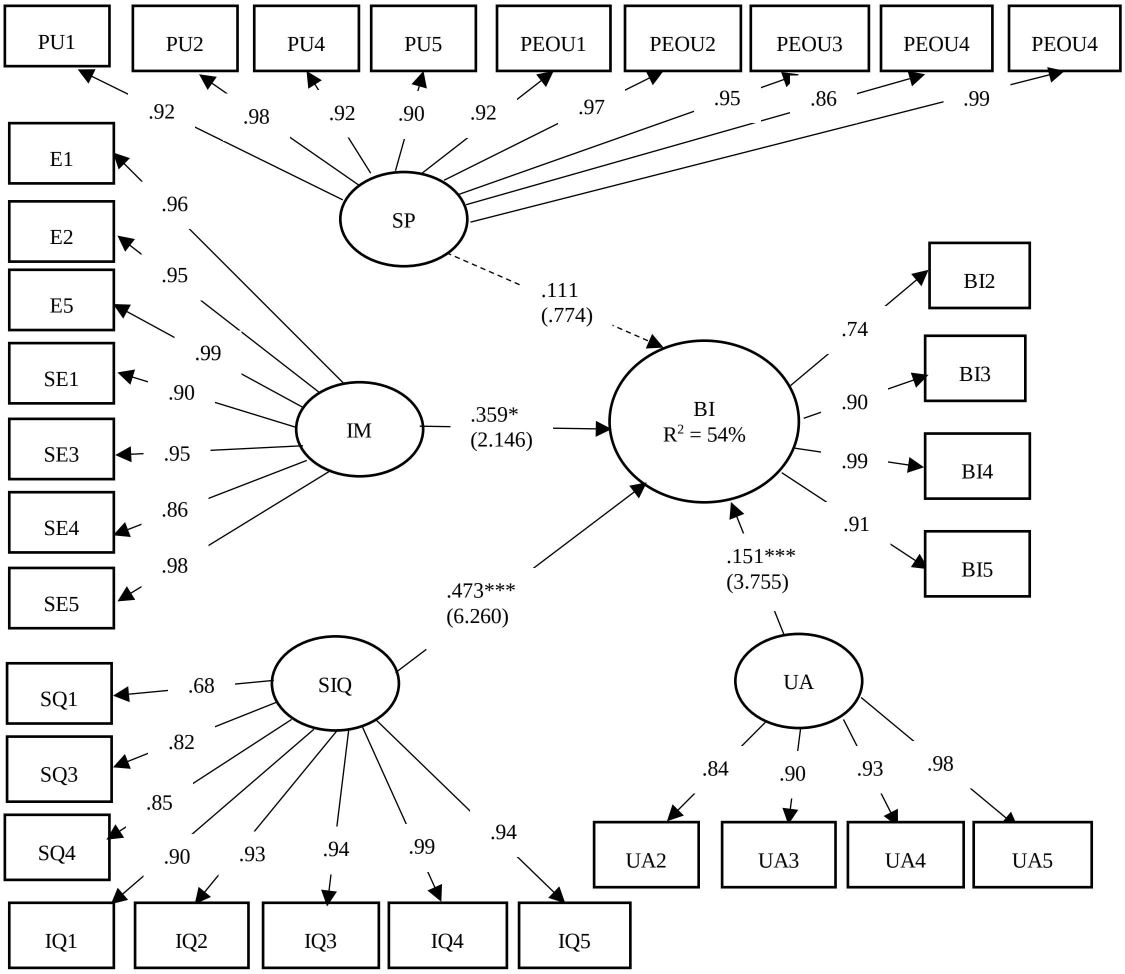

Figure 2. Updated framework and results of the structural equation model analysis.
Note. **p* < 0.05, ***p* < 0.01, ****p* < 0.001, *t* values in parentheses. Dashed path is not significant.

Development of measurement model

Analyses was conducted in two stages. In the first stage, all 38 items (excluding SE2 and BI1) were included in the measurement model, and were assessed and subjected to re-specification for revision and improvement. In the second stage, another round of confirmatory factor analysis was performed based on the re-specified model. All statistical analyses were set with an alpha level of .05. Maximum likelihood estimation was used to perform the CFA in this study. Multiple goodness-of-fit indices, residual error terms, modification indices, and their expected parameter changes were assessed and used to determine model fit. Due to the large sample size, the chi-square to degrees of freedom ratio (χ^2/df) was reported (Bentler, 1992), alongside goodness-of-fit index (GFI), normed-fit-index (NFI), comparative-fit-index (CFI), Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA).

The initial five-factor model with all 38 items showed χ^2 (730, N = 396) = 2592.85 and χ^2/df = 3.5, p < .001, suggesting a lack of fit between the model and the data. However, due to the sensitivity of χ^2 in large samples, other fit indices were assessed (Hair et al., 2006). Examination of these indices revealed slight poor fit with GFI = .74, NFI = .83, CFI = .87, TLI = .87, RMSEA = .08. All standardised item loadings were above .5. Examination of the modification indices revealed significant misfits and six items were subsequently removed. The re-specified model with 32 items presented substantial improvements in model fit, with χ^2 (485, N = 396) = 1280.20, χ^2/df = 2.6, p < .001. Examination of the indices showed acceptable model fit with GFI .83, NFI .90, CFI .93, TLI .93, and RMSEA 0.06. Given the significant improvement in overall fit, the re-specified model was considered the better model (Table 3).

Table 3
Summary of goodness-of-fit indices for the initial model and alternate model

	Goodness of Fit Measures					
Model	χ^2/df	GFI	NFI	CFI	TLI	RMSEA
Optimal value	< 3.0[a]	> .80[b]	> .90[c]	> .90[d]	> .90[e]	< .08[f]
Initial model, 38 items	3.5	.74	.83	.87	.87	.08
Re-specified model, 32 items	2.6	.83	.90	.93	.93	.06

Note. GFI = goodness-of-fit index; NFI = normed-fit-index; CFI = comparative-fit-index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation.
([a] Marsh & Hocevar, 1985; [b] Doll, Xia, & Torkzadeh, 1994; [c] Bentler & Bonett, 1980; [d] Bentler, 1992; [e] Hu & Bentler, 1999; [f] Byrne, 2001)

All factor loadings for each indicators were above .5, indicating high convergent validity (Byrne, 2001). Construct reliability (CR) of each factor was above .7, thus meeting the requirement for reliability (Hair et al., 2006). Table 4 displays the factor loadings of each factor and its construct reliability (CR).

Table 4
CFA - Standardised factor loadings and construct reliability

Factor	CR	Item	Standardised factor loading
System perception	0.984	PU1	0.92
		PU2	0.98
		PU4	0.92
		PU5	0.90
		PEOU1	0.92
		PEOU2	0.97
		PEOU3	0.95
		PEOU4	0.86
		PEOU5	0.99
Intrinsic motivation	.982	E1	0.96
		E2	0.95
		E5	0.99
		SE1	0.90
		SE3	0.95
		SE4	0.86
		SE5	0.98
System and information quality	0.967	IQ1	0.90
		IQ2	0.93
		IQ3	0.94
		IQ4	0.99
		IQ5	0.94
		SQ1	0.68
		SQ3	0.82
		SQ4	0.85
Uncertainty avoidance	0.953	UA2	0.84
		UA3	0.90
		UA4	0.93
		UA5	0.98
Behavioural intention	0.938	BI2	0.74
		BI3	0.90
		BI4	0.99
		BI5	0.91

Discriminant validity was performed next to determine the extent to which the factors are truly distinct from other factors in the model. The correlation coefficients *r* between two factors in the re-specified models are less than .9. An investigation of each pair of factors' average variance extracted (AVE) and their squared correlation coefficient r^2 revealed that the AVEs for each pair of factors to be greater than their r^2, thus preserving the discriminant validity of the re-specified model (Byrne, 2001; Fornell & Larcker, 1981). Table 5 presents the factors' AVE and each pair of the factor's r^2.

Table 5
AVE (on the diagonal) and r^2 (on the off-diagonal) among factors

Factors	SP	IM	SIQ	UA	BI
SP	**0.875**				
IM	0.372	**0.888**			
SIQ	0.203	0.240	**0.785**		
UA	0.194	0.230	0.240	**0.791**	
BI	0.026	0.026	0.026	0.084	**0.835**

Hypotheses test

To confirm the proposed hypotheses, SEM (structural equation modelling) was performed. Figure 2 shows the SEM results for the hypotheses. BI to use mobile technology in the classroom to promote interactions was jointly predicted by IM (β = .359) at the p < .005 significant level, SIQ (β = .473) at the p < .0001 significant level, and UA (β = .151) at the p < .0001 significant level. Therefore, hypotheses H2, H3, and H4 were supported. However, contrary to TAM, SP (conceptualised from perceived usefulness and ease of use) was found to have no significant effect on behavioural intention, resulting in the rejection of hypotheses H1.

Discussion

The present study was conceptualised to study factors believed to be decisive for affecting acceptance of technology in the classroom, with the focus on large lecturer classes prohibiting students from active discussions or interactions, particularly with their lecturers. Studies have proven the importance of perceived ease of use and usefulness in determining behavioural studies (Calisir et. al, 2014; Padilla-Meléndez et al., 2013; Tarhini et al., 2014). The TAM model has been adopted, replicated, and integrated in a wide variety of studies. Both factors have consistently been demonstrated as strong determinants across a wide range of technological studies. The present study failed to substantiate the traditional TAM and previous studies on the effects of perceived usefulness and perceived ease of use towards influencing higher education students' behavioural intention to use mobile technology in large lecturer classes to facilitate interaction among peers, and with their lecturers. Thus, rejection of hypotheses H1 may signify a shift in the thinking paradigm among adolescents and young adults who are adept and savvy with Web 2.0 tools and mobile devices.

Therefore, resistance towards new technology may not be as pivotal as it once was, and factors such as ease of use may no longer play a crucial role towards behavioural intention. For instance, ease of use was a weak predictor of attitude for determining user repurchase intention (Jang & Noh, 2011), and students' BI to use YouTube for procedural learning (Lee & Lehto, 2013). Popularity of mobile messaging applications such as WhatsApp and Facebook Messenger in Malaysia (Osman, Talib, Sanusi, Shiang-Yen, & Alwi, 2012; Saad, 2015) are indicative of existing use, thus suggesting that students' possess adequate computing technological expertise. Therefore, perception towards system usability and ease of use may not contribute to explaining a significant portion of BI variances of mobile technology among adolescents and young adults.

Current studies have proven enjoyment and self-efficacy as pivotal factors (Giesbers et. al, 2013; Sarwar et al., 2014). This may be reflective of the younger generation seeking instant gratification when it comes to technology use, and is indicative of the possibility that although mobile technology is beneficial in the classroom as instructional tools, if it does not excite the students or contain elements that promote enjoyment, BI may reduce as a consequence. Popularity of mobile messaging hinges on its ability for users to express themselves, pass time, or engage in an assortment of the services deemed attractive (Singh, 2014). The complexity of Facebook features have not deterred many from using it, and may reflect enjoyment and self-efficacy as success factors. Research conducted proved that Facebook remains the most popular choice of social media platform (Duggan, Ellison, Lampe, Lenhart, & Madden, 2015). This can be attributed to the fact that the quality and variety of services brings an element of fun and excitement for its user. Therefore, consistent with our prediction, enjoyment and adeptness at using mobile technology moderately predict behavioural intention in the present study.

Despite much focus on extrinsic and intrinsic motivators, the present study found that traditional factors of good quality of information and system design are critical in explaining the variances of BI. A review of literature in the area of mobile technology adoption for learning purposes reveals a lack of emphasis given to investigate the influence of information and system quality. SIQ is given much more focus when it comes to design and development of sophisticated information system, for instance an enterprise resource planning and decision support system (Olson & Staley, 2012; Van Valkenhoef, Tervonen, Zwinkels, De Brock, & Hillege, 2013). Consideration needs to be given to the analysis and design efforts, bearing in mind that essential qualities such as reliability, accuracy, relevancy, flexibility, and timeliness are essential. Considering that the present findings pointed to SIQ as strong predictors of BI, proper system development methodology for mobile applications development is important to aid developers in understanding user requirements.

The selection of UA was driven by the role of culture towards influencing organisational values, and secondly the recognition of UA in recent years as pivotal in technology acceptances studies. As expected, the sample data provided strong evidence that UA is significant, therefore validating previous researchers on the role of culture towards system acceptances. Therefore, understanding user requirements, and delivering mobile applications designed with the intended user in mind can thus reduce levels of uncertainty or hesitation. This differs from perceived ease of use or usefulness. The level of UA represents the willingness to embark on new experiences (Hofstede et al., 2010), or to try use new mobile tools particularly if the system usability is not clearly communicated to the user. To summarise, the hypotheses test using structural equation modelling indicates that system and information quality, together with IMs (enjoyment and self-efficacy) and low levels of UA contributes to the explanation of user exceptions, but perceptions of usefulness and ease of use does not.

Conclusions, limitations, and future work

Results from factor analysis loaded together items from perceived ease of use and perceived usefulness, indicative of the blurring distinction of these two constructs in the study of mobile technology acceptance in higher education. Another interesting observation was both self-efficacy and enjoyment items were loaded together as a single factor, indicative that self-confidence and enjoyment are tightly interconnected in explaining one's experience towards technology usage. However as predicted, items from information quality and system quality loaded together and suggest that for mobile applications, clear distinction of both constructs are not necessarily required, particularly mobile applications without complex functionalities. As the present study was to ascertain factors influencing mobile technology use in the classroom as a tool to facilitate interaction, functionality required is similar to that of mobile messaging applications. Therefore, distinction between the two factors may no longer be applicable within the context of the present study.

Interestingly, the β coefficients of SIQ/BI, IM/BI, and UA/BI were greater than SP/ BI . Therefore, findings suggest that the current paradigm in the investigation of success factors of technology acceptances may be slowly moving towards a focus on system design efforts, as well as influences of culture such as UA and IM. Findings are suggestive of students' accepting or rejecting mobile tools for interaction purposes in the classroom based on their overall assessment of how comfortable they feel and do they enjoy using such tools in the classroom, and also are the mobile tools efficient and produces useful information to support their learning endeavours. Perceptions of ease of use and usefulness as insignificant are suggestive of the young generation of technology user not minding exerting cognitive efforts, and reflects their confidence in using new mobile tools.

The present study put forth a framework with direct relationships between the independent and dependent variables. Future work of interest is to study the effects of information quality and system quality towards explaining perceived ease of use and perceived usefulness. It will be noteworthy to investigate the moderating effects UA has on system perceptions. Gender roles for comparative studies may produce interesting results, as are comparative analysis of students from the sciences and non-sciences discipline. Growing influences of culture on technology acceptance warrants in-depth study on its own, such as the correlation of students' personality towards technology acceptances. Invitation emails were sent to higher learning institutions located in urban areas with free Wi-Fi provided for its users. Therefore, the sample data may not be representative of students' of higher learning institutions located in rural areas. In-depth analysis in the present student is not possible to compare the various possible models. Furthermore, during the development of the measurement model, six items were removed to ensure model fit. Future work will involve using and comparing the results using alternative statistical software.

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References

Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision sciences*, *30*(2), 361-391. http://dx.doi.org/10.1111/j.1540-5915.1999.tb01614.x

Ariff, M. S. M., Yeow, S. M., Zakuan, N., Jusoh, A., & Bahari, A. Z. (2012). The effects of computer self-efficacy and technology acceptance model on behavioral intention in internet banking systems. *Procedia-Social and Behavioral Sciences, 57*, 448-452. http://dx.doi.org/10.1016/j.sbspro.2012.09.1210

Aykut, A. (2009). Cross-cultural analysis of european e-government adoption. *World Applied Sciences Journal*, *7*(9), 1124-1130. Retrieved from https://mpra.ub.uni-muenchen.de/20705/1/MPRA_paper_20705.pdf

Azjen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. http://dx.doi.org/10.1016/0749-5978(91)90020-T

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215. Retrieved from http://psycnet.apa.org/doi/10.1037/0033-295X.84.2.191

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, *28*(2), 117–148. http://dx.doi.org/10.1207/s15326985ep2802_3Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*, 1-26. http://dx.doi.org/10.1146/annurev.psych.52.1.1

Barnes, S. J., & Vidgen, R. (2012). User acceptance and corporate intranet quality: An evaluation with iQual. *Information & Management*, *49*(3), 164-170. http://dx.doi.org/10.1016/j.im.2012.02.002

Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. *Psychological Bulletin*, *112*(3), 400-404. http://psycnet.apa.org/doi/10.1037/0033-2909.112.3.400

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588-606. http://psycnet.apa.org/doi/10.1037/0033-2909.88.3.588

Biggs, J. (2012). What the student does: Teaching for enhanced learning. *Higher Education Research & Development*, *31*(1), 39-55. http://dx.doi.org/10.1080/07294360.2012.642839

Blasco-Arcas, L., Buil, I., Hernandez-Ortega, B., & Sese, F. J. (2013). Using clickers in class. The role of interactivity, active collaborative learning and engagement in learning performance. *Computers & Education*, *62*, 102-110. http://dx.doi.org/10.1016/j.compedu.2012.10.019

Byrne, B. M. (2001). Structural equation modeling with AMOS, EQS, and LISREL: Comparative approaches to testing for the factorial validity of a measuring instrument. *International Journal of Testing*, *1*(1), 55-86. http://dx.doi.org/10.1207/S15327574IJT0101_4

Calisir, F., Altin Gumussoy, C., Bayraktaroglu, A. E., & Karaali, D. (2014). Predicting the intention to use a web-based learning system: Perceived content quality, anxiety, perceived system quality, image, and the technology acceptance model. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *24*(5), 515-531. http://dx.doi.org/10.1002/hfm.20548

Celik, V., & Yesilyurt, E. (2013). Attitudes to technology, perceived computer self-efficacy and computer anxiety as predictors of computer supported education. *Computers & Education*, *60*(1), 148-158. http://dx.doi.org/10.1016/j.compedu.2012.06.008

Chilwant, K. S. (2012). Comparison of two teaching methods, structured interactive lectures and conventional lectures. *Biomedical Research*, *23*(3), 363-366. Retrieved from http://www.biomedres.info/abstract/comparison-of-two-teaching-methods-structured-interactive-lectures-and-conventional-lectures-1132.html

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, *23*(2) 145-158. http://dx.doi.org/10.2307/249749

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. http://dx.doi.org/10.2307/249008

DeLone, W. H., & McLean, E. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9-30. http://dx.doi.org/10.1080/07421222.2003.11045748

Detlor, B., Hupfer, M. E., Ruhi, U., & Zhao, L. (2013). Information quality and community municipal portal use. Government Information Quarterly, *30*(1), 23-32. http://dx.doi.org/10.1016/j.giq.2012.08.004

Dobson-Mitchell, S. (2011). Are big classes really a problem? Retrieved from http://www.macleans.ca/education/uniandcollege/are-big-classes-really-a-problem/

Doll, W. J., Xia, W., & Torkzadeh, G. (1994). A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly*, *18*(4), 453-461. http://dx.doi.org/10.2307/249524

Duggan, M., Ellison, N.B., Lampe, C., Lenhart, A., & Madden, M. (2015). Social media update 2014. Pew Research Center. Retrieved from http://www.pewinternet.org/2015/01/09/social-media-update-2014

Elavsky, C. M., Mislan, C., & Elavsky, S. (2011). When talking less is more: Exploring outcomes of Twitter usage in the large-lecture hall. *Learning, Media and Technology*, *36*(3), 215-233. http://dx.doi.org/10.1080/17439884.2010.549828

Fishbein, M., & Azjen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382-388. http://dx.doi.org/10.2307/3150980

Giesbers, B., Rienties, B., Tempelaar, D., & Gijselaers, W. (2013). Investigating the relations between motivation, tool use, participation, and performance in an e-learning course using web-videoconferencing. *Computers in Human Behavior*, *29*(1), 285-292. http://dx.doi.org/10.1016/j.chb.2012.09.005

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.

Hasan, B. (2006). Delineating the effects of general and system-specific computer self-efficacy beliefs on IS acceptance. *Information & Management*, *43*(5), 565-571. http://dx.doi.org/10.1016/j.im.2005.11.005

Hoftede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind* (3rd ed.). London: McGraw-Hill Education.

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers’ technology acceptance. *Journal of Research on Technology in Education*, *43*(4), 343-367. http://dx.doi.org/10.1080/15391523.2011.10782576

Hrastinski, S., & Aghaee, N. M. (2012). How are campus students using social media to support their studies? An explorative interview study. *Education and Information Technologies*, *17*(4), 451-464. http://dx.doi.org/10.1007/s10639-011-9169-5

Hsia, J. W., Chang, C. C., & Tseng, A. H. (2014). Effects of individuals' locus of control and computer self-efficacy on their e-learning acceptance in high-tech companies. *Behaviour & Information Technology*, *33*(1), 51-64. http://dx.doi.org/10.1080/0144929X.2012.702284

Hsu, M. H., & Chiu, C. M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems*, *38*(3), 369-381. http://dx.doi.org/10.1016/j.dss.2003.08.001

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55. http://dx.doi.org/10.1080/10705519909540118

Hwang, Y., & Lee, K. C. (2012). Investigating the moderating role of uncertainty avoidance cultural values on multidimensional online trust. *Information & management*, *49*(3), 171-176. http://dx.doi.org/10.1016/j.im.2012.02.003

Jang, H. Y., & Noh, M. J. (2011). Customer acceptance of IPTV service quality. *International Journal of Information Management*, *31*(6), 582-592. http://dx.doi.org/10.1016/j.ijinfomgt.2011.03.003

Johnson, I. Y. (2010). Class size and student performance at a public research university: A cross-classified model. *Research in Higher Education*, *51*(8), 701-723. http://dx.doi.org/10.1007/s11162-010-9179-y
Kline, R. B. (2005). *Principles and Practice of Structural Equation Modeling* (2nd ed.). New York, NY: The Guilford Press.
Laver, K., George, S., Ratcliffe, J., & Crotty, M. (2012). Measuring technology self-efficacy: reliability and construct validity of a modified computer self-efficacy scale in a clinical rehabilitation setting. *Disability and Rehabilitation*, *34*(3), 220-227. http://dx.doi.org/10.3109/09638288.2011.593682
Lean, O. K., Zailani, S., Ramayah, T., & Fernando, Y. (2009). Factors influencing intention to use e-government services among citizens in Malaysia. *International Journal of Information Management*, *29*(6), 458-475. http://dx.doi.org/10.1016/j.ijinfomgt.2009.03.012
Ledford, C. J., Saperstein, A. K., Cafferty, L. A., McClintick, S. H., & Bernstein, E. M. (2015). Any questions? An application of Weick's model of organizing to increase student involvement in the large-lecture classroom. *Communication Teacher*, *29*(2), 116-128. http://dx.doi.org/10.1080/17404622.2014.1003309
Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the technology acceptance model. *Computers & Education*, *61*, 193-208. http://dx.doi.org/10.1016/j.compedu.2012.10.001
Lin, W. S., & Wang, C. H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education*, *58*(1), 88-99. http://dx.doi.org/10.1016/j.compedu.2011.07.008
Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First-and higher order factor models and their invariance across groups. *Psychological bulletin*, *97*(3), 562-582. http://dx.doi.org/10.1037/0033-2909.97.3.562
Matusitz, J., & Musambira, G. (2013). Power distance, uncertainty avoidance, and technology: Analyzing Hofstede's dimensions and human development indicators. *Journal of Technology in Human Services*, *31*(1), 42-60. http://dx.doi.org/10.1080/15228835.2012.738561
Mun, Y. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies*, *59*(4), 431-449. http://dx.doi.org/10.1016/S1071-5819(03)00114-9
Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). New York, NY: McGraw Hill.
Olson, D. L., & Staley, J. (2012). Case study of open-source enterprise resource planning implementation in a small business. *Enterprise Information Systems*, *6*(1), 79-94. http://dx.doi.org/10.1080/17517575.2011.566697
Osman, M. A., Talib, A. Z., Sanusi, Z. A., Shiang-Yen, T., & Alwi, A. S. (2012). A study of the trend of smartphone and its usage behavior in Malaysia. *International Journal of New Computer Architectures and their Applications*, *2*(1), 274-285. Retrieved from http://sdiwc.net/digital-library/a-study-of-the-trend-of-smartphone-andits-usage-behavior-in-malaysia
Padilla-Meléndez, A., del Aguila-Obra, A. R., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education*, *63*, 306-317. http://dx.doi.org/10.1016/j.compedu.2012.12.014
Pai, F. Y., & Huang, K. I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650-660. http://dx.doi.org/10.1016/j.techfore.2010.11.007
Park, E., Baek, S., Ohm, J., & Chang, H. J. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics*, *31*(1), 3-15. http://dx.doi.org/10.1016/j.tele.2013.07.001
Park, S. Y., Nam, M. W., & Cha, S. B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology*, *43*(4), 592-605. http://dx.doi.org/10.1111/j.1467-8535.2011.01229.x
Pollock, P. H., Hamann, K., & Wilson, B. M. (2011). Learning through discussions: Comparing the benefits of small-group and large-class settings. *Journal of Political Science Education*, *7*(1), 48-64. http://dx.doi.org/10.1080/15512169.2011.539913
Rehman, R., Afzal, K., & Kamran, A. (2013). Interactive lectures: A perspective of students and lecturers. *Journal of Postgraduate Medical Institute*, *27*(2), 152-156. http://dx.doi.org/10.1080/15512169.2011.539913

Roopa, S., Bagavad Geetha, M., Rani, A., & Chacko, T. (2013). What type of lectures students want?-A reaction evaluation of dental students. *Journal of Clinical and Diagnostic Research*, *7*(10), 2244-2246. https://dx.doi.org/10.7860/JCDR/2013/5985.3482
Saad, W. Z. (2015, January). *Effective blended learning of microbiology using interactive Web 2.0 applications*. Paper presented at the International Conference on Advances in Education Technology (ICAET 2014), Bandung, West Java, Indonesia. Retrieved from http://www.atlantis-press.com/php/pub.php?publication=icaet-14&frame=http%3A//www.atlantis-press.com/php/paper-details.php%3Fid%3D16138
Sabiote, C. M., Frías, D. M., & Castañeda, J. A. (2012). The moderating effect of uncertainty-avoidance on overall perceived value of a service purchased online. *Internet Research*, *22*(2), 180-198. http://dx.doi.org/10.1108/10662241211214557
Sarwar, S., Razzaq, Z., & Saeed, I. (2014). Evaluation of interactive lectures: An innovative approach employed in a hybrid teaching system. *Pak J Physiol*, *10*, 3-4. Retrieved from http://pps.org.pk/PJP/10-3/Samia.pdf
Scott, W. E., Farh, J. L., & Podsakoff, P. M. (1988). The effects of "intrinsic" and "extrinsic" reinforcement contingencies on task behavior. *Organizational Behavior and Human Decision Processes*, *41*(3), 405-425. http://dx.doi.org/10.1016/0749-5978(88)90037-4
Singh, J. (2014). Mobile messaging through android phones: An empirical study to unveil the reasons behind the most preferred mobile messaging application used by college going students. *International Journal of Multidisciplinary and Current Research*, *2*, 367-372. Retrieved from https://ssrn.com/abstract=2411656
Tan, C. W., Benbasat, I., & Cenfetelli, R. T. (2013). IT-mediated customer service content and delivery in electronic governments: An empirical investigation of the antecedents of service quality. *MIS Quarterly*, *37*(1), 77-109 Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=3085&context=misq
Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach for an extended technology acceptance model. *Journal of Educational Computing Research*, *51*(2), 163-184. http://dx.doi.org/10.2190/EC.51.2.b
Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & Education*, *57*(2), 1645-1653. http://dx.doi.org/10.1016/j.compedu.2011.03.002
Turel, O., Serenko, A., & Giles, P. (2011). Integrating technology addiction and use: An empirical investigation of online auction users. *MIS Quarterly*, *35*(4), 1043-1062. Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=2994&context=misq
Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in Experimental Social Psychology*, *29*, 271-360. http://dx.doi.org/10.1016/S0065-2601(08)60019-2
Van Valkenhoef, G., Tervonen, T., Zwinkels, T., De Brock, B., & Hillege, H. (2013). ADDIS: A decision support system for evidence-based medicine. *Decision Support Systems*, *55*(2), 459-475. http://dx.doi.org/10.1016/j.dss.2012.10.005
Veletsianos, G., & Navarrete, C. (2012). Online social networks as formal learning environments: Learner experiences and activities. *The International Review of Research in Open and Distance Learning*, *13*(1), 144-166. http://dx.doi.org/10.19173/irrodl.v13i1.1078
Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research*, *11*(4), 342-365. http://dx.doi.org/10.1287/isre.11.4.342.11872
Wang, Y. S., Yeh, C. H., & Liao, Y. W. (2013). What drives purchase intention in the context of online content services? The moderating role of ethical self-efficacy for online piracy. *International Journal of Information Management*, *33*(1), 199-208. http://dx.doi.org/10.1016/j.ijinfomgt.2012.09.004
Wu, X., & Gao, Y. (2011). Applying the extended technology acceptance model to the use of clickers in student learning: Some evidence from macroeconomics classes. *American Journal of Business Education (AJBE)*, *4*(7), 43-50. Retrieved from http://search.proquest.com/docview/880545622?pq-origsite=gscholar
Yoo, S. J., Han, S. H., & Huang, W. (2012). The roles of intrinsic motivators and extrinsic motivators in promoting e-learning in the workplace: A case from South Korea. *Computers in Human Behavior*, *28*(3), 942-950. http://dx.doi.org/10.1016/j.chb.2011.12.015

Yoo, S. J., & Huang, W. H. D. (2011). Comparison of Web 2.0 Technology Acceptance Level based on Cultural Differences. *Educational technology & society*, *14*(4), 241-252. Retrieved from http://www.jstor.org/stable/jeductechsoci.14.4.241

Yoon, C. (2009). The effects of national culture values on consumer acceptance of e-commerce: Online shoppers in China. *Information & Management*, *46*(5), 294-301. http://dx.doi.org/10.1016/j.im.2009.06.001

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