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Validating a Structural Model of Using Mobile Technology for Learning among High School Students

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Despite the existing body of literature focusing on the effects of one-to-one mobile technology integration in teaching and learning, research discussed that the determinants of mobile technology acceptance and use in secondary school settings are still unclear. Hence, this study examined the extent to which determinants influence high school students' behavioral intention to use one-to-one mobile technology for learning. The newly proposed model incorporated three additional constructs beyond those in the unified theory of acceptance and use of technology (UTAUT) model, including computer self-efficacy, attitude toward using technology and computer anxiety, as suggested by recent literature. Data were collected from 247 U.S. Midwestern high school students who participated in an online survey. Using a structural equation modeling approach, this study established construct validity for the nine-construct extended UTAUT model to assess high school students' intention to use mobile technology. The results of structural relations in the proposed model showed that their behavioral intention to use mobile technology was significantly predicted by social influence and attitude toward using technology. Also, their strong behavioral intention and facilitating conditions were associated with frequent use of mobile technology in learning. Discussion, implications, and conclusion were addressed in this study.

Keywords : Technology acceptance, Mobile learning, One-to-one mobile technology, Secondary education, Structural equation modeling

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Introduction

Mobile learning refers to learning supported by portable mobile devices, such as iPod Touches, iPads, mobile phones, and laptop computers (Crompton & Keane, 2012; Sharples, Taylor, & Vavoula, 2007). The advent of mobile technologies enabled learners to take advantages of learning anytime and anywhere (Caudill, 2007; Sung, Chang, & Liu, 2016). Importantly, mobile technologies are expected to bridge learning in classroom, afterschool, and home-schooling environments when content and resources could be accessed from anywhere (Chou, Block, & Jesness, 2012). Hence, education departments in several states already started to implement one-to-one laptop initiative programs in K-12 schools (Russell, Bebell, & Higgins, 2004). Also, many researchers found that mobile learning can be affordable to support successful learning experience for students in K-12 schools (Crompton, Burke, & Gregory, 2017). Along with new trends of using mobile technologies at schools, numerous studies focused on the influences of one-to-one technology initiatives in teaching and learning. As a result, one-to-one mobile technology was found effective in enhancing teaching as well as supporting student-centered learning in various subjects, for example mathematics and history (King, Gardner-McCune, Vargas, & Jimenez, 2014; Song & Kim, 2015).

Despite a number of studies focusing on the effects of using mobile technology, little was known about what factors can influence user acceptance and actual use of mobile technology at secondary school settings. According to the literature related to mobile technology acceptance, Al-Emran, Mezhuyev, and Kamaludin (2018) found that understanding factors of mobile learning acceptance still remains uncertain and is a critical research issue in the field of educational technology. Understanding in-depth about mobile technology acceptance and use by end users is a prior process that can be connected to the successful integration of technology for teaching and learning. Specifically, Shin and Kang (2015) confirmed that students' higher behavioral intention to use learning technologies can contribute to improving learning outcomes. Hence, it is crucial that educational systems need to understand students' needs for supporting technology adoption, which can ultimately connect to successful learning experience (Hwang, Sung, Hung, & Huang, 2013; Nikou & Economides, 2017). On the other hand, several theoretical frameworks (e.g., technology acceptance models) exist, providing insight into user acceptance of information communication technology. However, although the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh, Morris, Davis, & Davis, 2003) has been prevalent to investigate new technology acceptance and use in various contexts (Cilliers, 2017; Lin, Lu, & Liu, 2013), its validation of the UTAUT model should be tested, especially in mandatory mobile learning environments (Dečman, 2015). We noted that research has been rare to date on the acceptance and use of technology in mandatory K-12 school environments applying comprehensive theoretical frameworks (Bervell & Umar, 2017; Dečman, 2015). Therefore, this study primarily aimed to examine the extent to which the constructs of a nine-construct extended UTAUT model (e.g., performance expectancy, effort expectancy, social influence, facilitating conditions, computer self-efficacy, attitude toward using technology, computer anxiety, and behavioral intention) predict high school students' use behavior of one-to-one mobile technology (e.g., Chromebooks) for learning.

Literature Review

The unified theory of acceptance and use of technology model

The UTAUT model has been widely accepted in a variety of contexts as the theoretical framework to explain individual differences associated with new technology acceptance and use behaviors (Wrycza, Marcinkowski, & Gajda, 2017). As seen in Figure 1, the core constructs of this model such as performance expectancy, effort expectancy, and social influence directly predict behavioral intention to adopt a technology tool, whereas facilitating conditions and behavioral intention directly affect the actual use of the tool. Gender, age, experience, and voluntariness of use serve as moderators. The definitions of the core constructs are as following:

- Performance expectancy is defined as the extent of one's belief that use of the technology will improve or her job performance;
- Effort expectancy refers to expected endeavor for using the technology;
- Social influence refers to an individual's perception if others people think he or she should use the technology; and
- Facilitating conditions is defined as one's belief about the presence of support within an organizational and technical infrastructure for using the technology (Venkatesh et al., 2003).

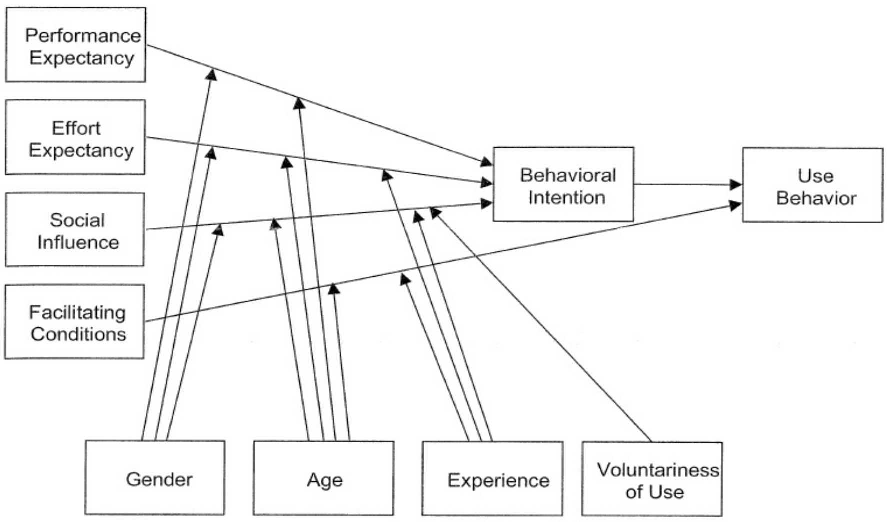

Figure 1. The original UTAUT model (Venkatesh et al., 2003)

The review of literature indicated that this model provided significant insight in assessing user acceptance of new technology systems in various educational settings.

For example, Birch and Irvine (2009) and Teo and Noyes (2014) examined the significant constructs that affect pre-service teachers' acceptance and integration of technology in teacher preparation. Modifying the original UTAUT model, Lin et al. (2013) investigated cognitive individual differences in e-learning information systems, while Rahman, Jamaludin, and Mahmud (2011) examined users' intention for using a digital library. Similarly, Wrycza et al. (2017) investigated university students' perceptions on the acceptance and use of new engineering software technologies in information technology education settings. The UTAUT model, generally regarded as a comprehensive user acceptance model of technology appeared to serve as a primary theoretical model to predict individual perceptions on the acceptance and use of new technology in different educational settings. However, recent research started to investigate factors beyond the UTAUT model because it appeared that some characteristics inherent in students were found to be important for the effective use of mobile technology (Bingimlas, 2009; Hew & Brush, 2007). More specifically, Gu, Zhu, and Guo (2013) indicated that personal and internal factors such as self-perceptions, self-efficacy, and attitudes about technology use in learning were significant to students. As a result, this study extended the UTAUT model by incorporating three critical personal factors. The following section discussed the potential influence of these factors.

Computer self-efficacy, attitude toward using technology, and computer anxiety

According to Bandura (1986), in social cognitive theory environmental factors (e.g., social pressures), cognitive and personal factors (e.g., individual perceptions), and behavior (e.g., using computers) influence reciprocally. Self-efficacy is defined as one's belief about his or her own ability to carry out a specific job (Bandura, 1986). More specifically, computer self-efficacy refers to "an individual's perceptions of his or her ability to use computers in the accomplishment of a task (e.g., using a software package for data analysis), rather than reflecting simple component skills (e.g., using a specific software feature such as bolding text or changing margins)" (Compeau & Higgins, 1995b, p. 191). Attitude toward use and an individual's evaluation of the behavior have been used to measure affective responses (Compeau, Higgins, & Huff, 1999). Attitude toward using a technology is defined as an individual's general emotional opinion toward using the technology (Venkatesh et al., 2003). Computer anxiety refers to fears of computers when using it (Chua, Chen, & Wong, 1999) or feelings of anxiety surrounding computers are expected to negatively influence computer use (Compeau & Higgins, 1995b). It is also defined as the tendency of a person to experience a level of uneasiness over his or her impending use of a computer (Howard & Smith, 1986). In other words, attitude toward using technology and computer anxiety can be considered as affective responses to certain behavior concerning with using one-to-one mobile technology in K-12 schools. The literature indicated that computer self-efficacy and anxiety were significantly associated with the acceptance of technology in computer supported learning environments (Celik & Yesilyurt, 2013). Attitude toward using technology was also known as playing a critical role in adopting mobile learning technology in most technology acceptance model (TAM) studies (Al-Emran et al., 2018).

Wang, Xu and Chan (2015) investigated whether computer self-efficacy could affect individual's intention to continuous use of social network sites. The results of hypothesis testing presented that computer self-efficacy had a significant effect on university students' intention for using the social network site through affection and cognition factors. However, computer self-efficacy did not affect the adoption and use of e-training for civil service individuals through perceived ease of use (Zainab, Awais Bhatti, & Alshagawi, 2017). Interestingly, Yukselturk and Altiok (2017) found that pre-service teachers' self-efficacy perceptions increased significantly after experiencing complex programming tasks, which contributed to significant decrease of negative attitudes toward programming tasks. Furthermore, Cazan, Cocoradă and Maican (2016) investigated the relationships between computer self-efficacy, computer anxiety, attitude toward the Internet among East European high school and university students. The results showed that low computer self-efficacy significantly predicted their computer anxiety and that computer anxiety was the strong predictor to negative attitude toward the Internet. Therefore, prior studies concerning with computer self-efficacy, attitude toward technology, and computer anxiety purported that it is necessary to assess how these constructs are associated with high school students' mobile technology acceptance and actual use behavior that may contribute to their performance.

Research Questions and Model

This study first proposed a nine-construct model by expanding the original UTAUT model with three additional constructs: computer self-efficacy, attitude toward technology, and computer anxiety (see Figure 2). In addition, the study aimed to provide empirical evidence of construct validity for the newly proposed model with the population of high school students in a U.S. Midwestern region and to examine the influences of the core constructs in predicting mobile technology acceptance and use behavior. The following research questions are addressed:

RQ1. To what extent can the nine-construct observed research model be validated to fit with the extended UTAUT model consisting of performance expectancy, effort expectancy, social influence, facilitating conditions, computer self-efficacy, attitude toward using technology, computer anxiety, behavioral intention and use behavior among high school students?

RQ2. To what extent do the main constructs of research model including performance expectancy, effort expectancy, social influence, and facilitating conditions predict behavioral intention and use behavior of mobile technology among high school students?

RQ3. To what extent do the additional constructs of research model including computer self-efficacy, attitude toward using technology, and computer anxiety predict behavioral intention and use behavior of mobile technology among high school students?

As presented in Figure 2, the following proposed research model was developed to be tested:

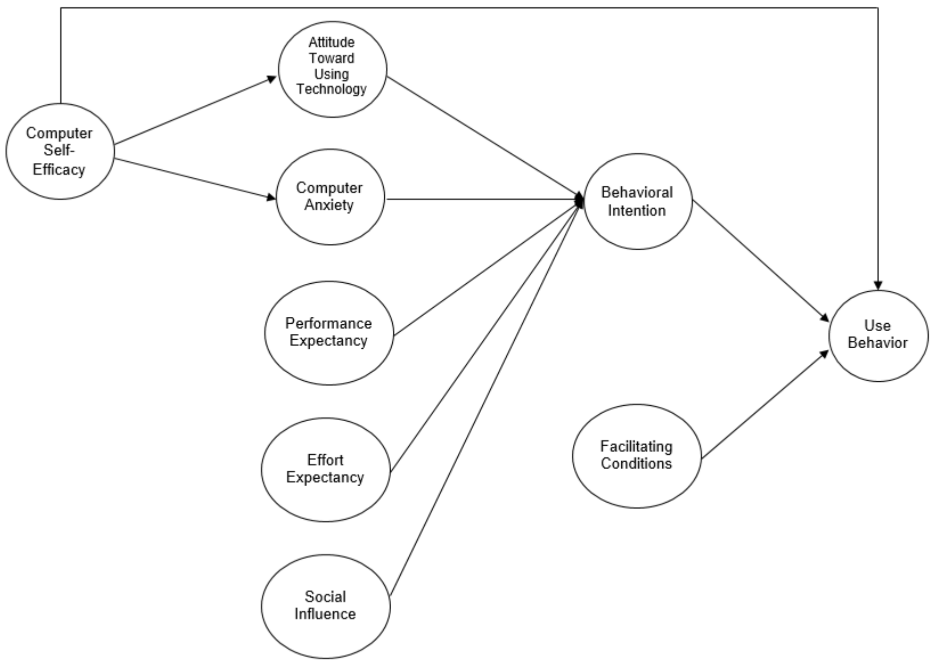

Figure 2. Research model

Methods

Participants and data collection

This study used a cross-sectional, non-experimental research design, using an online survey. The participants in this study were 260 students who regularly use one-to-one mobile technology (e.g., Chromebooks) for learning at a suburban high school in a U.S. Midwestern state. Thirteen students did not finish most of the survey items, hence 247 cases were used for a structural equation modeling analysis. Of 247 participants, 121 participants (48.9%) were female and 120 participants (48.5%) were male. Six cases (2.6%) did not disclose their gender and grades. Almost half of the participants were freshmen (N = 118; 48.7%). The next major participants were juniors (N = 79; 31.9%). Twenty-nine participants were seniors (11.7%) and 15 were sophomores (6.0%). A total of 49 survey items in the nine constructs presented in the proposed research model were used in the online survey. All the items were adopted from the Venkatesh et al.'s (2003) UTAUT model validation research and accordingly modified to this study context, except for the items of use behavior. Because use behavior was not specifically defined in previous studies, five items were developed to assess the frequencies of one-to-one mobile technology in the following areas: communication; classroom activities; information search for research; entertainment; and computer applications (e.g., online apps, cloud storage, online classroom, and word processing and presentation tools). After the Institutional Review Board approval was obtained from a university and permission from a school district was granted, high school students were asked to voluntarily participate in this study. The online survey was conducted to self-report in the items of the demographic item section and the nine-construct item section, using the seven-point Likert scale with a range from 1 (*strongly disagree*) to 7 (*strongly agree*).

Data preparation and analysis with structural equation modeling

This study employed a structural equation modeling approach to analyze data through Mplus version 7.4 (Muthén & Muthén, 2015), consisting of confirmatory factor analysis (CFA) to validate construct validity and structural equation modeling

(SEM) to assess structural relationships among the constructs of research model. A sample size should be dependent on a context of the obtained dataset, model complexity, multivariate normality, an estimation method, missing data, and average error variances of measured variables (Brown, 2015; Hair, Black, Babin, Anderson, & Tatham, 2010). Thus, the sample size of this study (N = 247) can be assumed to be in an appropriate range of 100 to 400 for using maximum likelihood or maximum likelihood robust estimation in SEM (Hair et al., 2010). Prior to SEM, the data screening process was conducted to determine an estimation method. Several missing cases and outliers were found, and multivariate outliers assumed to contribute to multivariate non-normality (Kline, 2016) were detected through Mahalanobis Distance (p<.01). Additionally, histograms, the Kolmogorov-Smirnov and the Shapiro-Wilk tests were conducted to assess univariate normality. The examination of variance inflation factor values was computed ranging from 1.55 to 7.60, which indicated there was no extreme multi-collinearity. Due to the assumption of multivariate non-normality of data, maximum likelihood robust estimation was determined to use for SEM (Allison, 2003; Muthén & Muthén, 2015).

The results of a measurement model by CFA can provide critical evidence for measurement model validity (Hair et al., 2010). Measurement model validity depends on achieving desirable levels of model fit statistics and providing evidence of construct validity, achieved by convergent validity and discriminant validity. To evaluate measurement model fit, the chi-square (χ^2) statistic and other fit indices (e.g., CFI, TLI, RMSEA, and SRMR) that Mplus yields were identified. For CFI, Hu and Bentler (1999) suggested that the minimum rule of thumb reasonable cut-off was .95 for a good model fit. In general, TLI values are lower than CFI values, but the recommended cut-off is the same as CFI (Wang & Wang, 2012). Hu and Bentler (1999) provided the cut-off RMSEA values for a good model fit as values less than .06. In addition, the extended criteria of RMSEA are often used as: 0 = perfect fit; < .05 = close fit; .05-.08 = fair fit; .08-.10 = mediocre fit; and >.10

= poor fit (MacCallum, Browne, & Sugawara, 1996). The cut-off value of SRMR for a good fit should be less than .08 (Hu & Bentler, 1999) and the value less than .10 could be acceptable (Kline, 2016). Convergent validity can be verified throughout acceptable factor loadings, construct reliability (McDonald, 1978), and average variance extracted (Fornell & Larcker, 1981). Discriminant validity is established as comparing average variance extracted values and the squared inter-correlations. Likewise, the results of SEM provided empirical evidence of structural model validity and statistical structural relationships among constructs in the current research model. To test structural model validity, we used the chi-square (χ^2) statistic and the same fit indices used in CFA. SEM provided the extent to which the constructs predict high school students' behavioral intention and use behavior of mobile technology for learning.

Results

Descriptive statistics and factor loadings

Initially, we computed the descriptive statistics and factor loadings of all measured items in each construct, including means, standard deviations, skewness, kurtosis, and univariate normality. Factor loadings over .70 could be considered high (Hair et al., 2010) and an acceptable level of factor loadings should be greater than .50 (Brown, 2015; Thompson, 2004; Wang & Wang, 2012). It is suggested that measured items affecting poor fit in the measurement model due to low factor loadings be removed and that there be at least three measured items in each construct for SEM (Brown, 2015). After removing poorly performing measured items with low factor loadings mostly less than .50, Table 1 presents constructs, item statements, descriptive statistics, and factor loadings of 29 measured items used for a final data analysis.

Table 1. Descriptive statistics and factor loadings of measured items (*N*=247)

Construct	Sample item statement	Item	Mean[a]/ SD[b]	Skewness/ Kurtosis	Factor loading[c]
Performance Expectancy (PE)	"I would find the use of Chromebook useful in my classes."	PE1	5.38/1.40	-.91/.25	**.802**
		PE5	4.90/1.46	-.63/.26	**.720**
		PE7	4.79/1.51	-.58/-.14	**.783**
		PE9	5.53/1.31	-1.01/1.11	**.828**
Effort Expectancy (EE)	"It is easy for me to become skillful at using Chromebook in my classes."	EE3	5.76/1.20	-1.25/1.84	**.757**
		EE5	5.63/1.30	-1.01/.76	**.893**
		EE6	5.79/1.11	-.82/.08	**.877**
Social Influence (SI)	"Teachers in this school have been helpful in the use of Chromebooks."	SI3	5.16/1.43	-.95/.71	**.796**
		SI4	5.45/1.16	-.38/-.66	**.736**
		SI5	5.65/1.06	-.60/-.37	**.911**
Facilitating Conditions (FC)	"I have the resources necessary to use Chromebook."	FC1	5.73/1.09	-.87/.14	.688
		FC2	5.99/.92	-.78/-.07	**.756**
		FC4	5.42/1.33	-.94/.87	.578
Computer Self-Efficacy (SE)	"I could complete a given task using Chromebook if no one tells me what to do."	SE1	5.47/1.34	-.80/.24	**.737**
		SE2	5.06/1.35	-.63/.19	.606
		SE3	5.22/1.36	-.78/.50	.536
Attitude Toward Using Technology (ATUT)	"Using Chromebook in my classes is a good idea."	ATUT1	5.33/1.36	-.78/.05	**.862**
		ATUT2	5.25/1.52	-1.13/1.05	**.858**
		ATUT4	5.10/1.55	-.79/.14	**.803**
		ATUT5	5.30/1.47	-.86/.52	**.809**
Computer Anxiety (ANX)	"Chromebook is somewhat intimidating to me."	ANX2	3.94/1.89	-.11/-1.10	.663
		ANX3	3.26/1.83	.46/-.81	**.929**
		ANX4	2.89/1.71	.58/-.65	**.850**
Behavioral Intention (BI)	"I intend to continue using Chromebook to work on classroom activities and assignments."	BI1	5.60/1.09	-.47/-.57	**.918**
		BI2	4.89/1.61	-.70/-.16	.463
		BI3	4.91/1.70	-.74/-.20	.533
Use Behavior (UB)	"I frequently use Chromebook for classroom activities such group projects."	UB2	5.83/1.09	-.89/.39	**.800**
		UB3	5.71/1.19	-.93/.33	**.765**
		UB5	5.96/1.16	-.97/-.07	**.818**

Note. Mean[a]: Possible range from 1 (*strongly disagree*) to 7 (*strongly agree*); SD[b]: Standard deviation; Factor loading[c]: All factor loadings significant ($p < .001$) and if greater than .70, factor loadings presented in bold.

Measurement model

The elimination of poorly performing measured items resulted in a better model fit for measurement model. Hence, the model fit indices show that the nine-construct observed research model fit adequately to the data (χ^2 [334] = 560.730, p < .001; CFI = .934; TLI = .920; RMSEA = .052; SRMR = .053). Table 2 displays internal consistency reliabilities (ICR), construct reliabilities (CR), average variance extracted (AVE), and squared inter-correlations (SIC) of the nine constructs to identify construct validity. Using Cronbach's α, ICR of scales (constructs) were computed. As an acceptable cut-off threshold for ICR, Cronbach's α = .70 is recommended (Kline, 1999), ICRs were sufficiently large, ranging from .712 and .916, except for the construct, facilitating conditions (α = .604). CR were computed as shown in the second bottom row of Table 2. The acceptable value of CR was greater or equal to .50, and a value greater than .70 was highly recommended (Hair et al., 2010). All constructs present good construct reliabilities with high values, ranging from .662 to 900. The latent constructs estimated AVE values. Using the recommended threshold for AVE that should be greater than .50 (Fornell & Lacker, 1981; Hair et al., 2010), three constructs, facilitating conditions (.459), computer self-efficacy (.399), and behavioral intention(.454) would have negative impacts on establishing convergent validity. However, considering collectively the results from the factor loadings of the measured items, ICRs, CRs, and AVE values of the nine constructs, convergent validity appears to be achieved. All pairs of AVE values were compared to the corresponding SICs. Although three constructs, facilitating conditions, computer self-efficacy, and behavioral intention seem to be less discriminable among the latent constructs, overall construct validity of the measurement appear to be identified. In short, these constructs appeared to have some negative impacts on construct validity, however they were hypothesized to serve as critical constructs in the proposed research model. Thus, the constructs, facilitating conditions, computer self-efficacy and behavioral intention were determined to continue to use in the structural model.

Table 2. Internal consistency reliabilities, construct reliabilities, average variance extracted, and squared inter-correlations of constructs (*N*=247)

Construct[a]	PE	EE	SI	FC	SE	ATUT	ANX	BI	UB
PE	.615								
EE	.446	.713							
SI	.225	.298	.668						
FC	.191	.362	.423	.459					
SE	.322	**.527**	**.425**	**.682**	.399				
ATUT	**.710**	.413	.234	.270	**.651**	.694			
ANX	.023	.094	.012	.137	.010	.015	.675		
BI	**.518**	.323	.452	**.488**	**.690**	**.664**	.030	.454	
UB	.267	.334	.358	**.491**	**.620**	.361	.031	**.719**	.631
CR[b]	.864	.881	.857	.716	.662	.900	.859	.695	.837
ICR[c]	.874	.877	.800	.677	.712	.916	.849	.745	.830

Note. Construct[a]: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; SE = Computer Self-Efficacy; ATUT = Attitude Toward Using Technology; ANX = Computer Anxiety; BI = Behavioral Intention; UB = Use Behaviors; CR[b] = Construct Reliability on the second bottom row; ICR[c] = Internal Consistency Reliability on the bottom row; Average Variance Extracted (AVE) on diagonal; Squared Inter-Correlations (SIC) on lower matrix; If either of AVEs ≤ corresponding SIC, SIC presented in bold.

Structural model

The model fit indices indicate that the proposed research model appears to fit acceptably to the data (χ^2 [350] = 637.534, p < .001; CFI = .916; TLI = .903; RMSEA = .058; SRMR = .066), so structural model validity could be achieved. As described in Figure 3, standardized path coefficients of this research model were assessed. In the structural model, social influence and attitude toward using technology had significant positive effects on high school students' behavioral intention to use mobile technology (β = .354, p < .001; β = .627, p < .001, respectively), while performance expectancy, effort expectancy, and computer anxiety had no statistically significant effects on behavioral intention to use mobile technology. Use behavior was significantly predicted by high school students' behavioral intention and facilitating conditions (β = .623, p < .001; β = .365, p

= .012, respectively). However, computer self-efficacy had no significant relationship with their actual use behavior concerning with mobile technology for learning. Interestingly, computer self-efficacy significantly predicted the different levels of attitude toward using technology and computer anxiety ($\beta = .872, p < .001$; $\beta = -.228, p = .011$, respectively). Also, computer self-efficacy had a significant indirect effect on high school students' intention to use mobile technology via attitude toward the technology ($\beta = .594, p < .001$). The proposed research model explained 74.5% ($R^2 = .745$) of the variance in behavioral intention by performance expectancy, effort expectancy, social influence, attitude toward using technology, and computer anxiety. Behavioral intention, facilitating conditions, and computer self-efficacy accounted for 71.6% ($R^2 = .716$) of the variance in use behavior in this research mode.

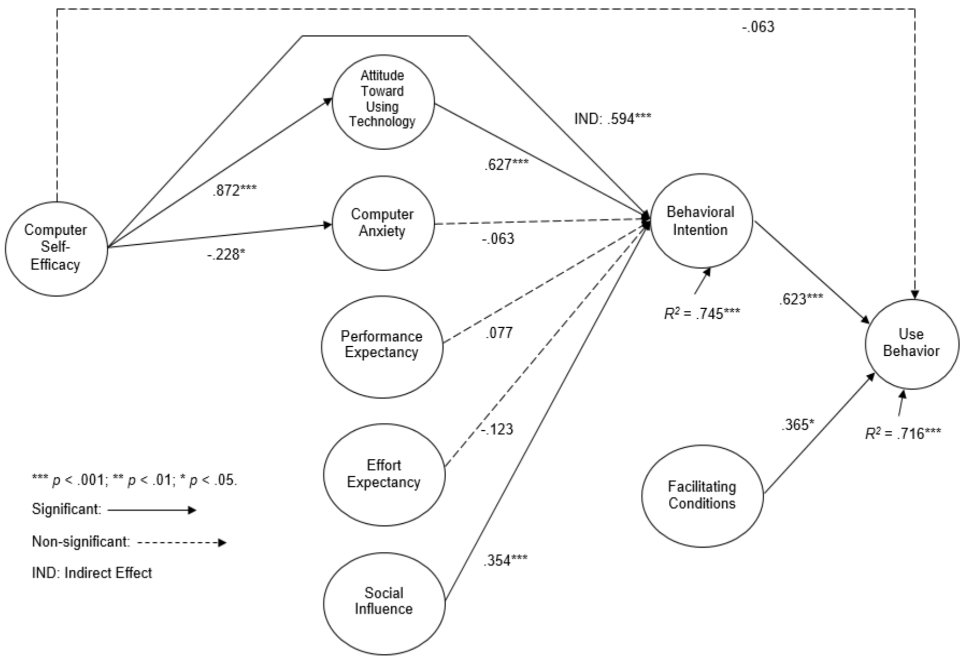

Figure 3. Standardized path coefficients of research model

Discussion

Effects of core constructs in the UTAUT model

This study primarily assessed the effects of core constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions on predicting U.S. Midwestern high school students' behavioral intention to use mobile technology for learning. Overall, the results of SEM supported that social influence was a significantly positive predictor associated with high school students' intention to use mobile technology. Clearly, behavioral intention had a strong positive relationship with their actual use behavior regarding one-to-one mobile technology in the classroom. The greater behavioral intention, the more frequently they use mobile technology in the classroom. Besides behavioral intention, facilitating conditions was considered as a core construct when they were actually using mobile technology for learning activities. Although prior research found that social influence was significant in mandatory settings like public education or institutional settings (e.g., Dečman, 2015; Venkatesh & Davis, 2000), this study stressed that influences from teachers, school leaders, or parents appear to be powerful to high school students' intention to use the technology. In other words, students may observe and consider teachers as important models of mobile technology use (Teo & Noyes, 2014). Hence, students can be encouraged to effectively use mobile technology for learning improvement by support from teachers who provide mobile technology-assisted learning opportunities (Nikou & Economides, 2017). The effect of facilitating conditions was consistent with Venkatesh, Brown, Maruping and Bala (2008) that technological and organizational infrastructure (e.g., skill improvement training, accessible information, available resources, and helpdesk support) can be influential for high school students' technology use in learning (Groves & Zemel, 2000). While, the findings of this study indicated that there were no significant influences of performance and effort expectancy on students' intention to use mobile technology. Surprisingly, there were no matters how perceived usefulness and ease of using the technology were influential for high school students even if performance and effort expectancy were stronger predictors on behavioral intention to use technology (Venkatesh et al., 2003). However, because high school students still rated performance and effort expectancy as highly important factors, this study suggested that students can be promoted to use mobile technology by focusing on functional and user-friendly aspects of using the technology to enhance learning performance.

Effects of computer self-efficacy, attitude toward using technology, and computer anxiety

This study also examined the effects of individual cognitive factors including computer self-efficacy, attitude toward using technology and computer anxiety on predicting high school students' intention to use mobile technology. As hypothesized in the nine-construct extended UTAUT model, this study confirmed that attitude toward using the technology had a significant effect on students' behavioral intention to use mobile technology, while computer anxiety had no significant effect on behavioral intention. Computer self-efficacy significantly predicted attitude toward using mobile technology positively and computer anxiety negatively, which was consistent with previous studies (see Cazan et al., 2016; Yukselturk & Altiok, 2017). Furthermore, computer self-efficacy indirectly influenced behavioral intention through students' attitudes toward mobile technology. Obviously, attitude toward using technology was the strongest predictor than any other predictors on assessing students' behavioral intention of technology use. Venkatesh et al. (2003) pointed out that although attitude toward using technology was yet the strongest predictor of behavioral intention in the nine-construct extended UTAUT model, the attitude construct tends to critically offset the effects of performance and effort expectancy on behavioral intention

(Zainab et al., 2017). Otherwise, attitude toward using technology predicting behavioral intention was significantly determined by perceived usefulness and perceived ease of technology use (Davis, 1989). Self-efficacy was used to assess an individual's capability to perform a specific behavior (Compeau & Higgins, 1995a; 1995b). In this study, computer self-efficacy was unique to the nine-construct research model predicting high school students' actual use of mobile technology. This non-significant relationship between computer self-efficacy and use behavior might be assumed that individuals with higher outcome expectations (e.g., performance expectancy) may be determined by prior experience or task familiarity (Compeau & Higgins, 1995a). If these possibilities were hypothesized, the effect of computer self-efficacy can be more accurately assessed on use behavior of mobile technology by high school students. Hence, students need to be promoted to participate in task-oriented activities because self-efficacy may be formed based on previous experience facilitating mastery experience and learning engagement (Scherer, Siddiq, & Tondeur, 2019). Like findings from Venkatesh et al. (2003), computer anxiety had no significant effect on behavioral intention because the effect of the anxiety construct could be possibly captured by effort expectancy.

Roles of the nine-construct extended UTAUT model

This study investigated the extent to which the nine-construct extended UTAUT model can be accounted for to explain high school students' behavioral intention to use one-to-one mobile technology for learning in a U.S. Midwestern region. The UTAUT model has been rarely used within educational settings to investigate students' intention to adopt and use specific technology. More interestingly, there has been little evidence to date to confirm if new technology acceptance and use was effective in secondary education. Hence, throughout this study, the nine-construct extended UTAUT model was found a comprehensive theoretical framework to understand U.S. Midwestern high school students' intention to use mobile technology for learning. The results of SEM showed that both of the nine-construct measurement and structural model fit acceptably to the data as providing construct validity and structural model validity evidence. In the nine-construct extended UTAUT model, the five constructs including performance expectancy, effort expectancy, social influence, attitude toward using technology, and computer anxiety contributed to a greater proportion of variance in high school students' intention to use mobile technology, compared to those in previous studies (e.g., Birch & Irvine, 2009; Teo & Noyes, 2014). Besides their behavioral intention, facilitating conditions and computer self-efficacy explained a considerably greater amount of variance in actual use behavior of mobile technology by high school students in learning activities (e.g., Venkatesh et al., 2003). Although these variances are unpredictable statistics among the constructs of the proposed research model, behavioral intention played a crucial role in understanding high school students' individual differences regarding the acceptance and use of mobile technology. Also, this study suggested that the nine-construct extended UTAUT model is expected to work as a useful framework if a decision-making process is essential for new technology adoption to students who is needed to innovative technology integration into learning at school or school district contexts. Likewise, Venkatesh et al. (2003) purported that the original UTAUT model could serve as a useful tool for organizations in business, training and marketing investigating the successful adoption of new technology in an attempt to understand target populations of users (e.g., employees) who may be reluctant to new information systems and develop supportive interventions. Overall, the nine-construct UTAUT model tested in this study was a partly useful theoretical framework in a mandatory learning environment. In addition, this model provided limited empirical evidence in understanding high school students' intention to use mobile technology for learning and considering important factors to design appropriate interventions to the actual target population of users.

Limitations and future directions

This study includes several limitations that could be possibly resolved in future research. First, the results, findings, and discussion of this study were drawn from a set of data collected from a specific target population of users, especially high school students in a U.S. Midwestern region. The participants in this study would likely have potential bias such as specific technology used for learning tasks at school that may be hardly linked to the generalization of understandings of individuals' behavioral intention to use technology (Wang, Wu, & Wang, 2009). Hence, future research needs to use random sampling methods to include more diverse aspects of learners at different levels and locations in which findings can be more generalizable. Second, because of a cross-sectional research design used in this study, the self-reported data from U.S. Midwestern high school students mirrored individuals' perceptions and behavioral intention to use technology at a certain time point. Regarding that individual perceptions and intention may change over time (Venkatesh et al., 2003), the UTAUT model including the proposed research model used in this study should be validated throughout different time points with other technology users in various educational settings. Also, Straub (2009) pointed out that the relation and direction between behavioral intention and use behavior sound infeasible because previous user experience may influence future behavioral intention for technology adoption and use. Hence, future studies need to use more powerful measures for making systematic approaches to examine either behavioral intention or use behavior. Third, this study did not examine the effects of moderators used in the UTAUT model such as gender, age, experience, and voluntariness of technology use on students' intention to use mobile technology. Especially, age and gender appeared to have significant influences in shaping individuals' intention to use technology (Dečman, 2015; Teo & Noyes, 2014; Venkatesh et al., 2003). Additionally, previous and current experience and voluntary conditions concerning with technology use across time may affect users' perceptions and intentions. Thus, future studies need to discuss about the effects of moderating factors differentiating relationships between constructs and behavioral intention. Lastly, despite the use of individual cognitive factors such as computer self-efficacy, attitude toward technology, and computer anxiety to predict users' intention, this study did not afford to provide prescriptive guidance to develop customized interventions to a target population of users. Thus, future research should include organizational outcomes and other cognitive factors (e.g., motivation and emotion) of broad target populations to design feasible interventions.

Conclusion

This study focused on the application of the nine-construct extended UTAUT model to understand how U.S. Midwestern high school students accept and use mobile technology. According to Pearson Education (2015), 22% of U.S. high school students used one-to-one laptop or tablet computers at school in 2015, even if more than 90% of them considered these technologies as "extremely important" or "very important" for learning. Prior to the adoption of new mobile technology, it was fundamental to identify the key constructs of the proposed UTAUT model affecting students' intention and actual use of mobile technology at school. First, this study assessed the effects of core constructs in the UTAUT model (e.g., performance expectancy, effort expectancy, social influence, and facilitating conditions) on predicting high school students' intention to use mobile technology. The findings showed that the social influence construct was a strong predictor to behavioral intention to use technology. Besides behavioral intention, the facilitating conditions construct had a significant positive effect on high school students' actual use behavior through mobile technology in learning activities. In addition, this study examined the effects of cognitive factors (e.g., computer self-efficacy, attitude toward using technology, and computer anxiety) on predicting students' behavioral intention of mobile technology use. This study found that the attitude construct was the strongest predictor to behavioral intention, while computer anxiety had no significant effect on intention. Although computer self-efficacy significantly predicted to the degrees of attitude toward technology positively and computer anxiety negatively, there was no significant relationship with high school students' actual use behavior of mobile technology in classroom activities. In conclusion, the nine-construct extended UTAUT model is considered as a partly useful theoretical model to understand high school students' intention to use mobile technology for learning. Moreover, it would be necessary that many other constructs from other theories or models still need to be investigated as complementary constructs to the original UTAUT model because the findings of this study provides empirical evidence for further studies related to mandated mobile technology adoption and use in secondary schools.

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