Article

Testing a Confirmatory model of Facebook Usage in SmartPLS using Consistent PLS

International Journal of Business and Innovation
3 (2) 01-13
2017
IRC Publisher
http://www.theijbi.net/

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Abstract

The purpose of this paper was to test a theoretical model of Facebook usage among university students in Malaysia using a confirmatory analysis. The theoretical model used to underpin the model was the parsimonius Technology Acceptance Model (Davis et al., 1989). We collected data from 600 undergraduate students of six public universities from Peninsular Malaysia using a structured questionnaire. Data were analyzed using SmartPLS 3.2.6 and instead of using the usual exploratory modeling analysis we used the more recent confirmatory analysis which is now available in SmartPLS called consistent PLS. Consistent PLS gives fit values that can be used to assess the model fit. The Standardized Root Mean Square Residual (SRMR = 0.03) was lower than 0.08 and the Normed Fit Index (NFI = 0.939) was higher than 0.90 thus we can conclude that the data fits the model well. The results show that ease of use influenced enjoyment but did not influence usage directly while usefulness influenced both enjoyment and usage directly and enjoyment also influenced usage directly. The R2 was 0.702 for enjoyment and 0.609 for usage. Implications of the findings are further discussed.

Keywords

Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, Usage, Facebook, Undergraduate Students, Malaysia.

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https://doi.org/10.65194/IJBI-2017-1004
Received 8 October 2016; Received in revised form 11 February 2017; Accepted 21 March 2017 2309-0693/

Introduction

Social network site (SNS) refers to any website that is used by Internet users to help them in creating their public profiles within the website and form relationships with other users who access their profiles. Although social networking websites are used to meet new people online, they are mainly about connecting with family, friends and acquaintances that they already have in the real lives. There are various famous social networking sites available and Facebook, Twitter, MySpace, Bebo are a few to name.

In Malaysia, social networking has become a central activity in Malaysians' lives. This is due to the development of technology throughout the world. According to Internet World Stats (2016), in 2016 the Malaysian population stood at 31 million and interestingly, the total number of Internet users was 21 million. Of this 21 million, a total of 19 million were Facebook users. It was also reported that Malaysians spend on average 159 minutes watching videos on the social media site (55% more than the global average) and Malaysians also have 1.6 times more friends than the global average.

The contribution of this paper is three-fold, 1. we model the predictors of social networking usage using the extented TAM, 2. previous research mostly used intention to use while our model used actual usage, 3. we apply and illustrate the latest analytical procedure available in SmartPLS 3.2.6 to do a confirmatory model analysis using the consistent PLS. The paper is organized as follows: the subsequent section presents the literature review and the theoretical development of this study which is then followed by methodology, findings and finally the discussion and conclusion.

Theory and Hypotheses Development

Technology Acceptance Model (TAM)

TAM was developed by Fred Davis and Richard Bagozzi (Bagozzi et al., 1992; Davis et al., 1989). The theory replaced TRA's attitude measures with the two technology acceptance measures which are perceived ease of use, and perceived usefulness. Research also indicated that TRA and TAM, both of which have strong behavioral elements, assume that when someone forms an intention to act, that they will be free to act without limitation. In reality, however, Bagozzi et al. (1992) argues that there will be many constraints, such as limit the freedom to act. Technology Acceptance Model (TAM) is tailored for an information systems theory that models how users come to accept and use a technology (Venkatesh, Morris, Davis & Davis, 2003). Several researchers have replicated Davis's original study (Davis, 1989) to provide empirical evidence on the relationships that exist between perceived usefulness, perceived ease of use and system use (Adams, Nelson, & Todd, 1992; Davis et al., 1989

TAM suggests that perceived usefulness and perceived ease of use determine an individual's intention to use a system. According to the TAM, these two beliefs are of primary significance for computer acceptance. Perceived usefulness (PU) was defined by (Davis, 1989) as the degree to which a person believes that using a particular system would enhance his or her job performance. Davis (1989) also defined perceived ease-of-use (PEOU) as the degree to which a person believes that using a particular system would be free from effort. Based on the Technology Acceptance Model (TAM), we derived our research model as shown in Figure 1.

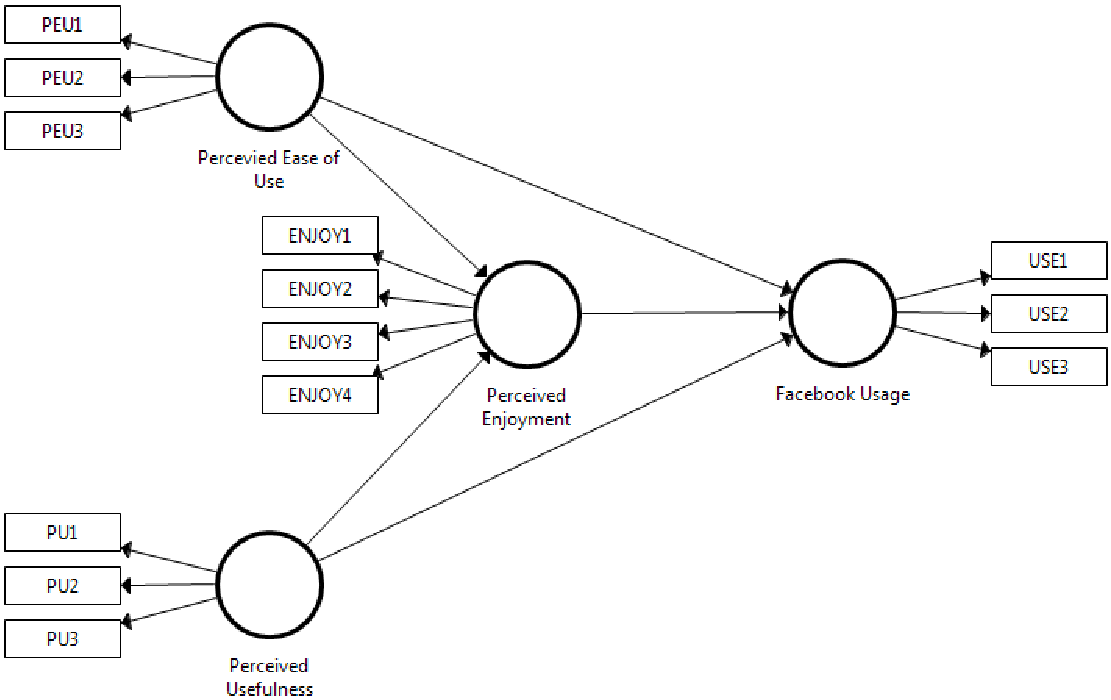

Figure 1 Research Model

Perceived ease of use (PEU)

Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). Effort is a finite resource that a person may allocate to the various activities for which he or she is responsible (Radner & Rothschild, 1975). All else being equal, an application perceived to be easier to use is more likely to be accepted by the users. Perceived ease of use has also been found to influence usage directly in different settings like e-book (Hsu et al., 2017), social network (Wambaa et al., 2017), smartwatch (Hong et al., 2017) and e-licensing technology (Muthu et al., 2016). It can be inferred that a system which is perceived easy to use will influence the enjoyment because systems that are difficult to use are less likely to be perceived as useful or enjoyable and thus lead to decreased usage. Thus, we hypothesize that:

H1: Perceived ease of use will have a positive effect on perceived enjoyment
H2: Perceived ease of use will have a positive effect on usage

Perceived Usefulness (PU)

Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Within the organizational context, a system that is high in perceived usefulness is one that the user believes will have a positive use-performance relationship. Past researches (Norazah et al., 2012; Chuah et al., 2016; Muthu et al., 2016; Hsu et al., 2017;

Wambaa et al., 2017; Hong et al., 2017;) has shown that perceived usefulness influences usage directly. Thus, we hypothesize that:

H3: Perceived usefulness will have a positive effect on perceived enjoyment
H4: Perceived usefulness of use will have a positive effect on usage

Perceived enjoyment

Perceived enjoyment is defined as the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated (Caroll & Thomas, 1988; Malone, 1981). A person will be motivated to do or repeat an activity which is enjoyable more as compared to the same activity which is not enjoyable. Teo (2001) found that Singapore Internet users use internet because it is perceived to be enjoyable while Wambaa et al. (2017) inferred that enjoyment important in social network usage. Interestingly also, Hong et al. (2017) revealed that enjoyment was important in smartwatch adoption while Alzahrani et al. (2017) found that enjoyment was important in online game playing. Thus, for this research we hypothesize that:

H5: Perceived enjoyment will have a positive effect on usage

Methodology

For the purpose of this study, data were collected from 6 public universities in Peninsular Malaysia using an intercept survey by using self-administered questionnaire. To calculate sample size we used the *G*power 3.1* (Faul et al., 2007; 2009) software with the setting as follows: f^2 = 0.02 (small), α = 0.05 and number of predictors = 3 and the power was set at 80% (Gefen et al., 2011), the sample size required to test this model was 550. From each university, we collected 100 responses which gave us a total sample size of 600. We selected 3 "research universities" and 3 "non-research universities" to provide a better representation of students. The questionnaire was divided into 3 sections; Section A (demographic information), Section B (information about perceived usefulness, perceived ease of use and perceived enjoyment) and Section C (information related to Usage). The items used to measure perceived usefulness and perceived ease of use were adapted from Davis (1989) and Igbaria et al. (1995). Respondents were asked to indicate their agreement or disagreement with several statements on a five-point Likert scale ranging from 1=strongly disagree to 5=strongly agree. Perceived enjoyment was measured using 4 different pairs of a seven point semantic differential scale adopted from Teo (2001). Facebook usage was measured using 3 items, 1. How many times do you use SNS during a week?, 2. How many hours do you use SNS every week? And 3. How frequently do you use SNS? (Teo, 2001).

Analysis and Results

As suggested by Hair et al. (2017) and Cain et al. (2016) we assessed the multivariate skewness and kurtosis using the software available at: https://webpower.psychstat.org/models/kurtosis/results.php?url=fb9771ad65087c96bdc6a313929fa338. The results showed that the data we have collected was not multivariate normal, Mardia's multivariate skewness (b= 2.854, p< 0.01) and Mardia's multivariate kurtosis (b= 31.075, p< 0.01), thus we proceeded to use SmartPLS which is a non-parametric analysis software.

To analyze the research model we used the Partial Least Squares (PLS) technique using the SmartPLS 3.2.6 software (Ringle, Wende & Becker, 2015). Following the recommended two-stage analytical procedures by Anderson and Gerbing (1988), we tested the measurement model (validity and reliability of the measures) followed by an examination of the structural model (testing the hypothesized relationship) (see Hair et al., 2017; Ramayah et al., 2011; 2013). Besides, to test the significance of the path coefficients and the loadings a bootstrapping method (5000 resamples) was used (Hair et al., 2017).

Measurement Model Analysis

To assess the measurement model two types of validity were being examined - first the convergent validity and then the discriminant validity.

Convergent Validity

The convergent validity of the measurement is usually ascertained by examining the loadings, average variance extracted (AVE) and also the composite reliability (Gholami et al., 2013). The loadings were all higher than 0.708, the composite reliabilities were all higher than 0.7 and the AVE of all constructs were also higher than 0.5 as suggested in the literature (see Table 1 and Figure 2).

Table 1
Convergent Validity

Constructs	Items	Loadings	Cronbach	rhoA	CR	AVE
Perceived Enjoyment	ENJOY1	0.941	0.969	0.969	0.969	0.886
	ENJOY2	0.953				
	ENJOY3	0.931				
	ENJOY4	0.939				
Perceived Ease of Use	PEU1	0.867	0.930	0.933	0.931	0.818
	PEU2	0.888				
	PEU3	0.956				
Perceived Usefulness	PU1	0.862	0.910	0.912	0.911	0.773
	PU2	0.923				
	PU3	0.85				
Facebook Usage	USE1	0.854	0.892	0.892	0.892	0.733
	USE2	0.866				
	USE3	0.847				

Discriminant Validity

There has been a recent criticism of that the Fornell-Larcker (1981) criterion do not reliably detect the lack of discriminant validity in common research situations (Henseler et al., 2015). They have suggested an alternative approach, based on the multitrait-multimethod matrix, to assess discriminant validity in the form of heterotrait-monotrait ratio of correlations. Henseler et al. (2015) also went on to demonstrate the superior performance of this method by means of a Monte Carlo simulation study. As such we have also tested the discriminant validity using this new suggested method and the results are shown in Table 2. If the HTMT value is greater than $HTMT_{0.85}$ value of 0.85 (Kline 2011), or $HTMT_{0.90}$ value of 0.90 (Gold et al., 2001) then there is a problem of discriminant validity. As all the values passed the $HTMT_{0.90}$ (Gold et al., 2001) and also the $HTMT_{0.85}$ (Kline, 2011) shown in table 2 indicating that discriminant validity has been ascertained.

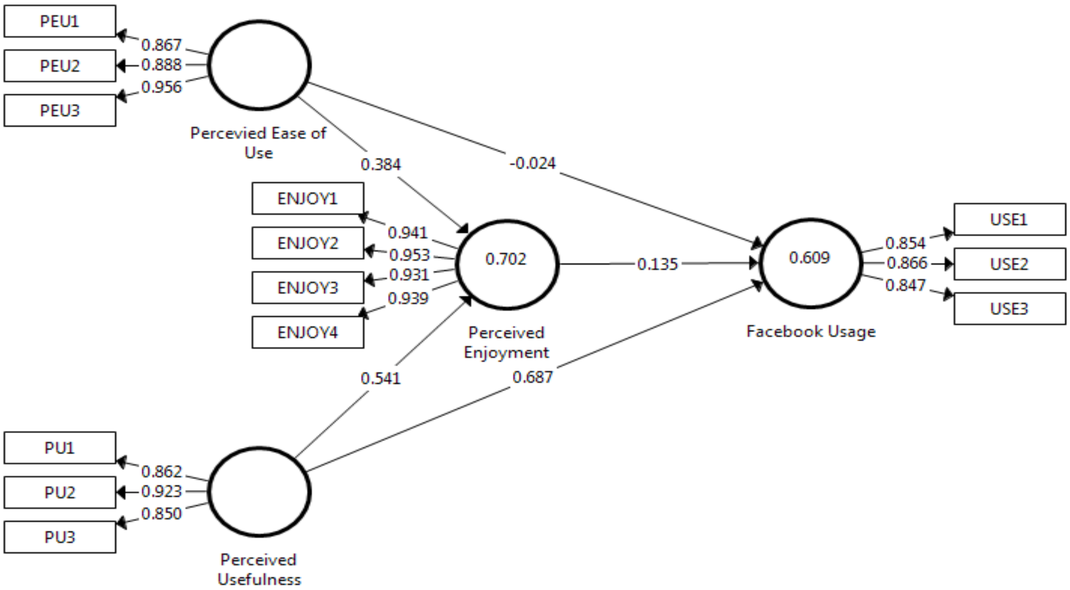

Figure 2 Measurement Model Results

Table 2

Discriminant Validity (HTMT Ratio)

	1	2	3	4
1. Facebook Usage				
2. Perceived Enjoyment	0.655			
3. Perceived Usefulness	0.776	0.784		
4. Perceived Ease of Use	0.507	0.726	0.634	

Structural Model Analysis

Testing Model Fit

Before proceeding to test the model, we first tested model fit by using three model fitting parameters: one is the Standardized Root Mean Square Residual (SRMR), second is the Normed Fit Index (NFI) and third the exact model fit (bootstrapped based statistical inference). The SRMR is defined as the difference between the observed correlation and the model implied correlation matrix whereby values less than 0.08 (Hu & Bentler, 1998) are considered a good fit. Henseler et al. (2014) introduced the SRMR as a goodness of fit measure for PLS-SEM that can be used to avoid model misspecification. The second fit index is normed fit index (NFI) an incremental fit measure which computes the Chi-square value of the proposed model and compares it against a meaningful benchmark (Bentler & Bonett, 1980). NFI values above 0.9 usually represent acceptable fit. The third fit value is exact model fit which tests the statistical (bootstrap-based) inference of the discrepancy between the empirical covariance matrix and the covariance matrix implied by the composite factor model. Dijkstra and Henseler (2015a; 2015b) suggested the *d_LS* (i.e., the squared Euclidean distance) and *d_G* (i.e., the geodesic distance) as the two different ways to compute this discrepancy. A model fits well if the difference between the correlation matrix implied by the model being tested and the empirical correlation matrix is so small that it can be purely attributed to sampling error thus the difference between the correlation matrix implied by your model and the empirical correlation matrix should be non-significant ($p > 0.05$). Henseler et al. (2016) that d_{ULS} and d_G < than the 95% bootstrapped quantile (HI 95% of d_{ULS} and HI 95% of d_G)

Since we have a saturated model with no free paths, the saturated model (measurement) fit values and the estimated model (structural model) fit values were exactly the same. The SRMR value was 0.030 (< 0.08) and the NFI was 0.939 (> 0.90) and the d_{ULS} < bootstrapped HI 95% of d_{ULS} and d_G < bootstrapped HI 95% of d_G indicating the data fits the model well.

Hypothesis Testing Results

To assess the structural model, Hair et al. (2017) suggested looking at the R^2, beta and the corresponding t-values via a bootstrapping procedure with a resample of 5,000. They also suggested that in addition to these basic measures researchers should also report the predictive relevance (Q^2) as well as the effect sizes (f^2). As asserted by Sullivan and Feinn (2012), while a *p*-value can inform the reader whether an effect exists, the *p*-value will not reveal the size of the effect. In reporting and interpreting studies, both the substantive significance (effect size) and statistical significance (*p*-value) are essential results to be reported (p.279). Hahn and Ang (2017) have summarized some of the recommended rigor in reporting results in quantitative studies which includes the use of replication studies, the use of effect size estimates and confidence intervals, the use of Bayesian methods, Bayes factors or likelihood ratios, and decision-theoretic modeling.

As suggested we have included effect sizes and confidence intervals as part of our reporting (see Table 3). Perceived ease of use ($\beta = 0.384$, $t = 7.971$, $p < 0.01$, $f^2 = 0.289$) and perceived usefulness ($\beta = 0.541$, $t = 13.112$, $p < 0.01$, $f^2 = 0.476$) positively influenced perceived enjoyment explaining 70.2% of the variance in enjoyment. This gives support for H1 and H3.

Next we looked at the predictive effects on the usage. Perceived usefulness (β = 0.687, t = 12.109, p < 0.01, f^2 = 0.276) and perceived enjoyment (β = 0.384, t = 1.960, p< 0.05, f^2 = 0.029) were significant while perceived ease of use (β = -0.024, t = 0.720, p > 0.05, f^2 = 0) was insignificant predictor of usage explaining 60.9% of the variance in usage. The findings support H4 and H5 while H2 is not supported.

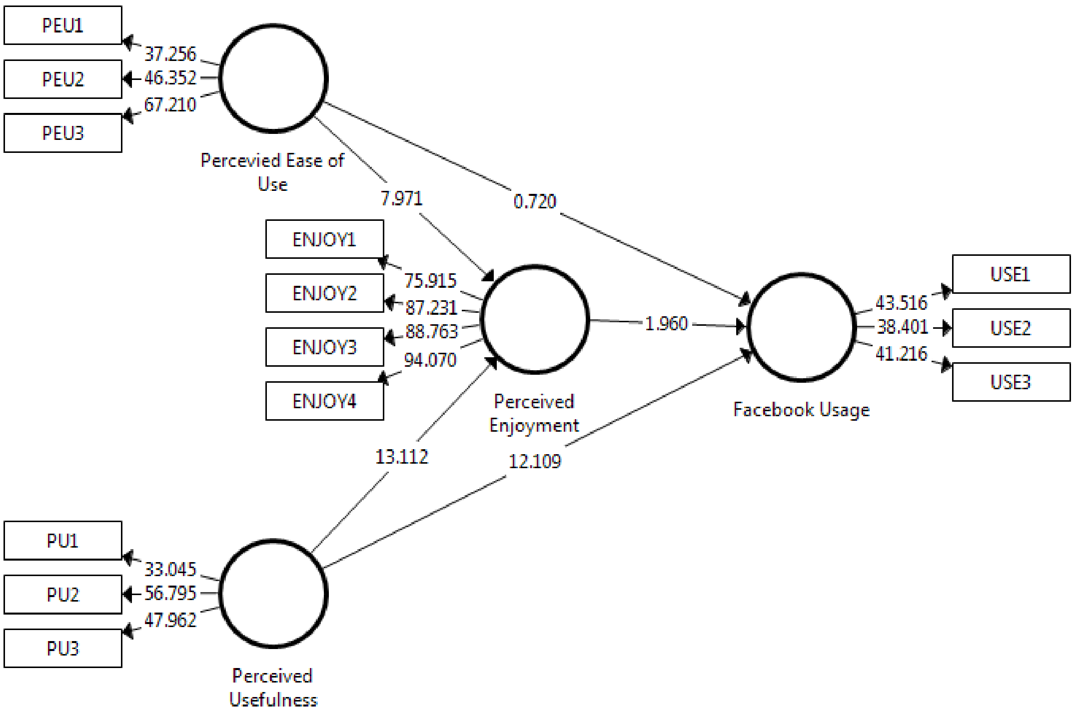

Figure 3 Bootstrapping Results

Table 3
Results of the hypothesis testing

Hypothesis	Relationship	Std. Beta	Std. Error	t-value	Decision	2.50%	97.50%	VIF	R^2	Q^2	f^2
H1	PEU → PE	0.384	0.048	7.971**	Supported	0.290	0.475	1.518			0.289
H2	PU → PE	0.541	0.041	13.112**	Supported	0.453	0.618	1.518	0.702	0.554	0.476
H3	PEU → Usage	-0.024	0.034	0.720	Supported	-0.083	0.000	1.957			0
H4	PU → Usage	0.687	0.057	12.109**	Supported	0.580	0.801	2.240	0.609	0.396	0.276
H5	PE → Usage	0.135	0.069	1.960*	Supported	0.012	0.270	2.818			0.029

Discussion and Conclusion

Our contribution in this paper was three-fold, thus we will discuss each of them in greater detail here.

Firstly, we developed an extended model of TAM to model Facebok usage by adding perceived enjoyment to the model. Our findings show that both perceived usefulness and perceived ease of use predicting perceived enjoyment. This finding is similar to the earlier studies like Hsu et al. (2017), Wambaa et al. (2017) and Hong et al. (2017). This confirms our prediction that perceived ease of use and usefulness of a system are important in driving enjoyment. All being equal, a systems which is easier and more useful to a user the more enjoyable will be the experience in using the system.

Next, we found perceived usefulness and perceived enjoyment to predict Facebook usage which is similar to the research of other researchers like Muthu et al. (2016) in e-licensing technology adoption, Hsu et al. (2017) in e-book adoption, Wambaa et al. (2017) is social network usage, Hong et al. (2017) and Chuah et al. (2016) in smartwatch adoption and Alzahrani et al. (2016) in online playing context. Previous literature also provides support to the idea that a system that is more useful and enjoyable, the more usage of the system.

Surprisingly, perceived ease of use was not found to be a significant predictor of Facebook usage. This finding can possibly be attributed to the profile of the respondents that consists of young undergraduates, the Gen-Ys who grew up with all the latest technology and tools, hence, presumably the perceived ease of use is not very important to them as they are very quick to adapt and learn new technologies compared to the older generation of user's.

The second contribution was that instead of using intention to use as the dependent variable, we modeled 3 items of usage as the dependent variable. The first item assessed how many times used, the second item assessed how many hours used and the third item assessed how frequently Facebook was used. This approach adds value in the sense that it provides more specific, holistic quantifiable measures of Facebook usage. This is in response to previous criticism that most researchers stop at intention to use and the intention to use does not necessarily leads to usage.

Our third contribution was the application of a confirmatory analysis using Consistent PLS (Dijkstra & Henseler, 2015a; 2015b) and to illustrate clearly how to do the analysis and report the findings. Other researchers who plan to use PLS to do more confirmatory models can follow the process shown in this paper.

Acknowledgements

This study is supported through the Fundamental Research Grant Scheme (FRGS) Phase 1/2014 granted by the Ministry of Education, Malaysia (203/PMGT/6711400).

References

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived Usefulness, Ease of Use, and Usage of Information Technology: A Replication. *MIS Quarterly*, 16(2), 227-247.

Alzahrani, A. I., Mahmud, I., Ramayah, T., Alfarraj, O., & Alalwan, N. (2017). Extending the Theory of Planned Behavior (TPB) to Explain Online Game Playing among Malaysian Undergraduate Students. *Telematics and Informatics,* 34(4), 239-251.

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, 103 (May), 411-423.

Bagozzi, R. P., Davis, F. D., Warshaw, P. R. (1992). Development and test of a theory of technological learning and usage. *Human Relations*, 45(7), 660-686.

Bentler, P. M., & Bonett, D. G. (1980). Significance Tests and Goodness-of-Fit in the Analysis of Covariance Structures. *Psychological Bulletin*, 88, 588-600.

Cain, M. K., Zhang, Z., & Yuan, K. H. (2016). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*, doi:10.3758/s13428-016-0814-1

Caroll, J. M., & Thomas, J. C. (1988). Fun. *SIGCHI Bulletin*, 19, 21-24.

Chuah, S. H.-W, Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: the role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, 65, 276–284

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease Of Use, And User Acceptance Of Information Technology. *MIS Quarterly* 13(3)*, 319–340.*

Davis, F. D., Bagozzi, R. P., Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical models, *Management Science,* 35(8), 982-1003.

Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, 81(1), 10-23.

Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modelling. *MIS Quarterly*, 39(2), 297-316.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41, 1149-1160.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39, 175-191. D

Fornell, C. G., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An Update and Extension to SEM Guidelines for Administrative and Social Science Research. *MIS Quarterly*, 35(2), iii-A7.

Gholami, R., Sulaiman, A. B., Ramayah, T., & Molla, A. (2013). Senior managers' perception on green information systems (IS) adoption and environmental performance: Results from a field survey*. Information and Management*, 50(7), 431-438.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: an organizational capabilities perspective. *Journal of Management Information Systems*, 18(1), 185–214.

Hahn, E. D., & Ang, S. H. (2017). From the editors: New directions in the reporting of statistical results in the Journal of World Business. *Journal of World Business*, 52, 125–126.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling. 2nd Edition. Thousand Oaks: Sage.

Hair, J. F., Thomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (2nd ed.). Thousand Oakes, CA: Sage.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial Management & Data Systems*, 116 (1), 2-20,

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Hong, J-C., Lin, P-H., & Hsieh, P-C. (2017). The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch. *Computers in Human Behavior*, 67, 264-272

Hsu, C-L, Lin, Y-H., Chen, M-C., Chang, K-C., & Hsieh, A-Y. (2017). Investigating the determinants of e-book adoption. *Program*, 51(1), DOI: http://dx.doi.org/10.1108/PROG-04-2014-0022

Hu, L.-T., & Bentler, P. M. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychological Methods*, 3(4), 424-453.

Igbaria, M., Zinatelli, N., Cragg, P., & Cavaye, A. L. M. (1997). Personal Computing Acceptance Factors in Small Firms: A Structural Equation Modeling. *MIS Quarterly*, 21, 3, 279-305.

Internet Word Stats (2016). Internet Users in Asia 2016. Available: http://www.internetworldstats.com/stats3.htm (Accessed 15 February 2016)

Kline, R. B. (2011). Principles and practice of structural equation modeling. New York: Guilford Press.

Malone, T. W. (1981). Toward a theory of intrinsically motivating instruction. *Cognitive Science*, 4, 349-361

Muthu, P. P., Ramayah, T., Alzahrani, A. I., Alfarraj, O., & Alalwan, N. (2016). E-Government service delivery by a local government agency: the case of E-Licensing. *Telematics and Informatics*, 33(4), 925–935.

Norazah M. S., Ramayah, T., & Ly, K. K. (2012). Empirical Investigation on Factors Influencing the Behavioral Intention to Use Facebook. *Universal Access in the Information Society Journal*, 11(2), 223-231.

Radner, R., & Rothschild, M. (1975). On the allocation of effort. *Journal of Economic Theory*, 10, 358-376.

Ramayah, T., Lee, J. W. C., Boey, J. C. I. (2011). Network collaboration and performance in the tourism sector. *Service Business*, 5(4), 411-428.

Ramayah, T.,Yeap, J. A. L., & Ignatius, J. (2013). An empirical inquiry on knowledge sharing among academicians in higher learning institutions. *Minerva: A Review of Science, Learning and Policy*, 51(2), 131-154.

Ringle, C.M., Wende, S., & Becker, J.-M. (2015). “SmartPLS 3,” www.smartpls.com

Sullivan, G. M., & Feinn, R. (2012). Using Effect Size - or why the p Value is not enough. *Journal of Graduate Medical Education*, 4(3), 279–282.

Teo, T. S. H. (2001). Demographic and motivational variables associated with Internet usage activities, *Internet Research: Electronic Networking Applications and Policy*, 11(2), 125-137.

Viswanath, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27(3), 425-478.

Wambaa, S. F., Bhattacharya, M., Trinchera, L., & Ngai, E. W. T. (2017). (2017). Role of intrinsic and extrinsic factors in user social media acceptance within workspace: Assessing unobserved heterogeneity. *International Journal of Information Management*, 37, 1–13.