

An Analysis on the Adoption of Software as a Service (SaaS) by the students of the State Universities in the North and Eastern Part of Sri Lanka

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Abstract: Software as Service (SaaS) as an option of cloud computing has been in use as one of the most advanced technology innovations by many users and organizations. Due to its scalability and network-based operation, SaaS provides many advantages for students and teachers in the universities for academic purpose without costly investment on IT infrastructure and expertise. The research aims at analyzing the adoption of SaaS using a theoretical framework by the students in the state universities located in the North and Eastern part of Sri Lanka and the PLS-SEM was used as the analytical tool for this study. The theoretical framework was developed based on the original Technology Acceptance Model (TAM) [1]. The data were obtained from 300 undergraduates of three state universities using a structured questionnaire. The collected data were analyzed utilizing the Smart PLS 3.2.7 with consistent PLS algorithm (PLSc). The results revealed that perceived ease of use, perceived usefulness, and perceived enjoyment directly influenced the SaaS adoption. It was also identified that there was specific indirect effect with the inclusion of perceived enjoyment as a mediating variable to SaaS adoption and it had significant effect and the research contributes to knowledge in the areas of Information Technology adoption studies.

Keywords: Perceived Ease of Use, Perceived Usefulness, Perceived Enjoyment, SaaS, TAM

Introduction

Software-as-a-Service (SaaS) as one of the cloud services models has gained the growth momentum during the last few years. Adoption of SaaS increases throughout the world along with increased users demand due to its inherent benefits that users can obtain from it and it has now become a matured market offering. Google Apps, Dropbox, Salesforce, Cisco WebEx, Concur, GoToMeeting are some of the examples for SaaS. Software as a Service (SaaS), uses provider's applications running on a cloud infrastructure where the applications are accessible from a thin client interface, such as a web browser (e.g., web-based e-mail), or a program interface [2]. A market survey done by Forbes predicted that the CAGR of SaaS applications would be almost at 21% in 2015-2020. Moreover, it was expected that the largest segment of the cloud

market with the revenue expected to grow 22.2% to reach \$73.6 billion from SaaS in 2018. Gartner has predicted that the adoption of would hit the expenses for applications by 45% by the year 2021 [3].

Cloud computing has become an important innovation used by many users and organizations. Software as Service (SaaS) as one of the service options has attained the prominence among diverse spectrum of users since its inherent nature of scalability and network-based operation. The service model SaaS has been very advantageous for students and teachers in the universities including on time accessibility to computing services as one of the latest technologies without costly investment on IT infrastructure and expertise. Most of the state universities in Sri Lanka have contracted to Google Apps and Microsoft 365 and lecturers and students use these cloud services for teaching and learning.

The issue focused in this research is in theoretical nature while determining the factors that influence the SaaS adoption also emphasized as operational importance. Further, understanding the right cause for the adoption of SaaS would enable the SaaS vendors to encourage and keep their users with them and other providers to enhance their services.

The contribution of this research falls into three domains. The study contributes to technology adoption model as an extended TAM model is developed to predict SaaS adoption using the original TAM constructs in the very first instance. The second contribution is the direct consideration of the adoption while previous researches mostly used TAM Model with the endogenous variable "intention". Third contribution is to make use of PLS-SEM analysis as an advanced method available for researchers with the help of Smart PLS 3.2.7 with the inclusion of Confirmatory Factor Analysis (CFA) using the consistent PLS with Structural Equation Modelling. This research paper has been arranged in the following sequences. The next section sheds light on previous literature and the theoretical development of this research and the methodology section follows. The final sections focus on the findings, discussion and conclusion respectively.

Literature Review and Hypotheses Development

Technology Acceptance Model (TAM)

Many researches on technology innovation adoption have been done using different technology adoption models. Cloud computing is also no exception as one the latest technologies with specific area of cloud computing. Further, these models such as TAM, TPB, UTAUT etc. were able to predict the adoption of cloud computing by considering different factor from the perspective of users and organization. Bhattacharjee & Park [4] have found the reasons for

the acceptance and usage from the model of client-server to cloud computing services [4], Giessmann & Stanoevska [5] did a research on customer preferences in adopting PaaS as a cloud offering and Behrend et al. [6] analyzed the student behavior in the adoption of SaaS as the cloud offering using TAM. Similarly, Wu et al. [7] came out with a technology acceptance model combining TAM with other variables and tested it. Moreover, the variable intention was tested with a sample of university students to adopt cloud storage [8].

Fred Davis and Richard Bagozzi originally proposed Technology Acceptance Model (TAM) [9, 1]. The TAM included two main technology acceptance constructs called perceived ease of use, and perceived usefulness leaving attitude proposed in TRA. Further, models like TRA and TAM had robust behavioral elements and assumed that users are free to act with no any constraints once they have formulated intention. However, many researchers are against to this view and assume that many constraints might control the liberty to act specific behavior [9] and Technology Acceptance Model (TAM) was originally developed for an information systems theory to check how users accept and use a new technology [10]. The constructs perceived usefulness and perceived ease of use that were included in the original TAM [11] were used by many other researchers to validate the relationships between those constructs and adoption of new technology empirically [12, 1].

Moreover, TAM was able to predict the individual intention to use a new system or technology with the help of perceived usefulness and perceived ease. Accordingly, these two variables of the TAM are very main determinants when considering any computing related technology like cloud computing. Perceived usefulness (PU) was explained as the extent to which a person believes that using a particular system would enhance his or her job performance [11]. Perceived ease-of-use (PEOU) was explained as the extent to which a person believes that using a particular system would be free from effort [11]. Based on the Technology Acceptance Model (TAM), the following extended Conceptual Framework (CF) was developed to examine the SaaS adoption as shown in Figure 1.

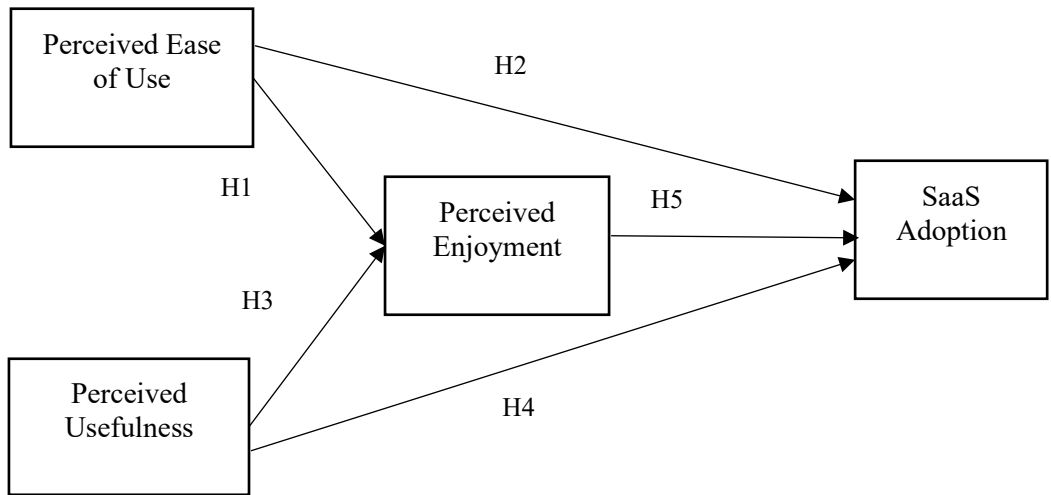


Figure 1: Conceptual Framework

Perceived Ease of Use (PEU)

Davis [11] defined perceived ease of use as the degree that a person believes that using a particular system would be free from effort. According to Radner & Rothschild [13], effort referred to the finite resource that a person would spare to the several tasks to which he or she is assigned. If an application is perceived to be easy to use, the users are more likely to be accepted and use it while other factors are being equal. Perceived ease of use has also been identified as an influencing factor of many technological innovation directly from different perspectives and settings. Accordingly, Hsu et al., [14] studied e-book adoption, Wambaa et al., [15] studied social network, Hong et al., [16] analyzed smartwatch, and Muthu et al., [17] studied e-licensing technology. Further, it could be assumed that a new technology which is viewed as easy to use would enable the users to get the enjoyment and systems or technology that are perceived as difficult to learn and use are less likely to be viewed as useful or enjoyable and thus, in the context of SaaS adoption as one of the cloud offerings lead to decreased SaaS adoption. Hence, the following hypothesis is proposed.

- H1: Perceived ease of use has an effect on perceived enjoyment
- H2: Perceived ease of use has an effect on SaaS adoption

Perceived Usefulness (PU)

Davis [11] explained perceived usefulness as the degree to which a person believes that using a particular system would increase his or her job performance. Previous researches [18, 19, 17, 14, 15,16] has found that perceived usefulness impacts the adoption of SaaS directly. For example, Davis [11] found that perceived usefulness was significantly correlated with both self-reported information system adoption and self-predicted future technology adoption. Similarly, Igbaria et al. [21] found that perceived usefulness has strong direct effects on personal computing adoption dimensions. Igbaria et al. [22] and Adams et al. [12] also confirmed that perceived usefulness is positively related to system or technology adoption. Hence, the following hypothesis is proposed.

- H3: Perceived usefulness has an effect on perceived enjoyment
- H4: Perceived usefulness of use has an effect on SaaS adoption

Perceived Enjoyment (PENJO)

As per Carroll & Thomas [23] and Malone [24], perceived enjoyment is viewed as the degree of pleasure that an activity he or she involves in when using the computer and it is perceived as enjoyable in addition to the other effects including performance that may be expected. A person is likely to get motivated to involve or redo an activity which is pleasurable more in contrast to an activity that is not enjoyable. Teo [25] found that internet users in Singapore use internet because it is perceived to be enjoyable while Wambaa et al. [15] found that enjoyment was an important determinant in social network adoption. Further, Hong et al. [16] found that enjoyment was a prominent determinant in smartwatch adoption while Alzahrani et al. [26] found that enjoyment was important in online game playing. Moreover, further supportive literature from various researches supports this argument [25]. The following hypotheses are developed for testing form the conceptual framework.

- H5: Perceived enjoyment has an effect on SaaS adoption
- H6: Perceived Enjoyment mediates the Perceived Ease of Use to SaaS adoption
- H7: Perceived Enjoyment mediates the Perceived Usefulness to SaaS adoption

Methodology

For the purpose of this study, data were collected from 3 state universities in the North and Eastern part of Sri Lanka using an online self-administered survey questionnaire. The total population sampling was used

since the researcher wanted to target all the undergraduates who use SaaS and do not use and exact number is not known as purposive sampling technique since most of the SaaS users share the same characteristics from the three state universities in the North and Eastern part of Sri Lanka. The questionnaire was divided into two sections; Section A (demographic profiles), Section B (Questions related to the constructs: perceived usefulness, perceived ease of use and perceived enjoyment, and SaaS adoption). The items used to measure variables were obtained from previous literature [11] and Igbaria et al., [21]. Survey participants were requested to mention their agreement or disagreement with the statements related to the constructs in the model on a five-point Likert scale ranging from 1=strongly disagree to 5=strongly agree.

Analysis and Results

The survey using online self-administered questionnaire produced data from 318 respondents from the population targeted and the usable responses were only 300 and the rest were discarded due to various flaws in the responses. For analysis, SPSS 23 and SmartPLS 3.2.7 software were used. As a first step in the data analysis, the coded data were entered into the SPSS 23 for further analysis and the data were screened for outliers and extreme values and done the necessary adjustments. Further, the skewness and kurtosis values were examined to check the normal distribution of data and the values were within +/-1. As per the recommendation by Hair et al. [27] and Cain et al. [28], the data were analyzed for the multivariate skewness and kurtosis using the software SmartPLS 3.2.7 since it has built-in functionality and the results were also within +/- 1.

The proposed model was tested with the Partial Least Squares (PLS) and Structural Equation Modelling (SEM)- PLS-SEM technique with the help of the SmartPLS 3.2.7 software [29]. Anderson and Gerbing [30] recommended two -stage analytical procedures suggested in this regard. At the first stage, the validity and reliability of the measures was tested from the measurement model and then the structural model was tested in order to test the hypotheses in the second stage [27, 31]. Further, the significance of the path coefficients and the loadings were tested using the bootstrapping procedure with the sample of 5000 resamples [27].

Descriptive Analysis

Respondents were asked to answer the questions in Section A of the Questionnaire for some baseline information. The following Table 1 provides the summary of the findings.

Table1: Demographic profile of respondents

Variables		Frequency	Percentage
Gender	Male	158	57%
	Female	142	43%
Age (in years)	Below 20	6	2%
	20 - 25	278	93%
	26 - 30	12	4%
	Above 30	4	1%
SaaS Adoption	Yes	268	89%
	No	32	11%
Types of SaaS Adoption	Google Mail and Google Docs	251	94%
	Microsoft Outlook / Hotmail and Microsoft 365	17	6%

Measurement Model Analysis

Measurement model analysis is the first step in the PLS-SEM procedure and the measurement model involves in assessing all the individual latent constructs in the model. First off, the two types of validity: convergent and discriminant and the construct reliability were assessed for the constructs in the model and the results are as follows.

Construct reliability and validity

The factor loadings were assessed to confirm the convergent validity of the measurement along with Average Variance Extracted (AVE) and the Composite Reliability (CR) were also examined [32, 33]. Accordingly, the loadings of all the items that measured the constructs were well above 0.7, the values of composite reliabilities were all higher than 0.7 and the AVE of all constructs were also higher than 0.5 as per the requirements to exists in the literature. The detailed scores have been given in the Table 2 and the Figure 2).

Table 2: Construct reliability and validity

Constructs	Items	Loadings	Cronbach's Alpha	rhoA	CR	AVE
Perceived Ease of Use	PEU1	0.849	0.836	0.836	0.836	0.629
	PEU2	0.777				

Perceived Usefulness	PEU3	0.762				
	PU1	0.811	0.839	0.841	0.839	0.635
	PU2	0.768				
Perceived Enjoyment	PU3	0.800				
	PENJO1	0.880	0.894	0.898	0.894	0.679
	PENJO2	0.767				
	PENJO3	0.765				
SaaS Adoption	PENJO4	0.878				
	USE1	0.795	0.867	0.869	0.866	0.619
	USE2	0.713				
	USE3	0.840				
	USE4	0.795				

Discriminant Validity

The Fornell-Larcker [34] criterion was used to assess the discriminant validity [34]. In the recent past, there has been arguments related to the Fornell-Larcker criterion since it does not reliably reflect the lack of discriminant validity [35] and the Heterotrait-Monotrait Ratio (HTMT) of correlations was recommended instead based on the multitrait-multimethod matrix to assess discriminant validity.

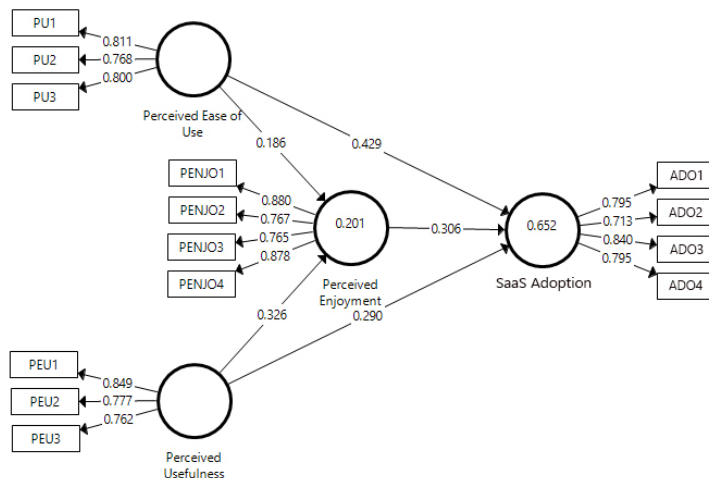


Figure 2: Measurement Model Results

Table 3: Discriminant Validity (HTMT Ratio)

	SaaS Adoption	Perceived Ease of Use	Perceived Enjoyment	Perceived Usefulness
SaaS adoption				
Perceived Ease of Use	0.682			
Perceived Enjoyment	0.575	0.345		
Perceived Usefulness	0.628	0.499	0.419	

Hence, the discriminant validity was assessed using HTMT criterion and all the results are clearly below the conservative threshold of 0.85 [27] and can be concluded that discriminant validity has been established as shown in Table 3 above.

Final Measurement Model

Finally, the Consistent PLS bootstrapping was run to test the measurement model's significance and the results shows that all the loadings of the items of the constructs are significant ($P < 0.05$). The collinearity statistics (VIF) for the outer model were below the threshold value of 5 suggesting that collinearity not at a critical level. The final measurement model is shown in Figure 3 below.

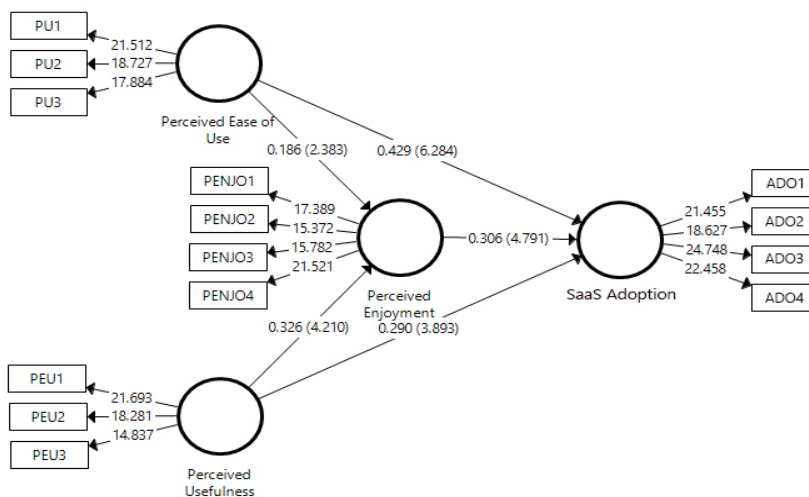


Figure 3: Final Measurement Model

Structural Model Analysis

Following the confirmation with the measurement model, structural model was tested and the results of the structural model analysis: model fit and hypotheses testing are presented in the subsequent sections. The following Figure 4 shows the results of the structural model obtained using consistent bootstrapping algorithm.

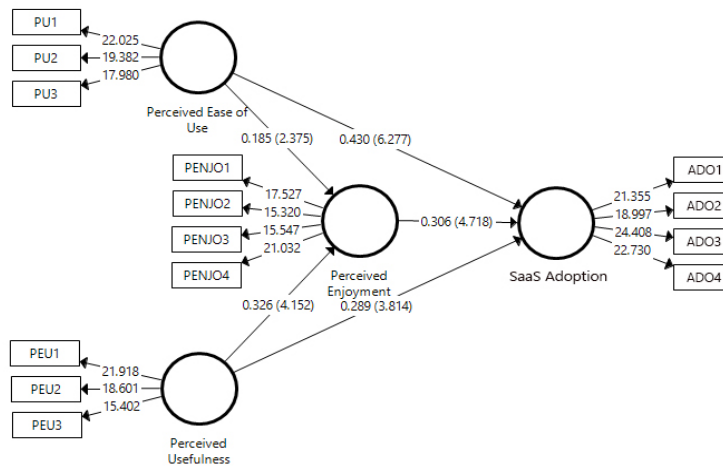


Figure 4: Bootstrapping Results

Testing Model Fit

PLS-SEM analysis produces some model fit indices such as Standardized Root Mean Square Residual (SRMR), the Normed Fit Index (NFI) etc. to assess the goodness of the fit. For this research, the model fit was assessed using SRMR and NFI. The SRMR is defined as the difference between the observed correlation and the model implied correlation matrix whereby values less than 0.08 [37] are considered a good fit. Henseler et al. [35] 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 [38]. NFI values above 0.9 usually represent acceptable fit. As per the results of the analysis, the SRMR value was 0.035 (SRMR < 0.08) and the NFI value was 0.922 (NFI > 0.9) suggesting acceptable fit of the model.

Hypothesis Testing Results

Hair et al. [27] suggested looking at the R^2 , beta (β) and the corresponding t-values via a bootstrapping procedure with a resample of 5,000 to assess the structural model with some additional statistical results such as the predictive relevance (Q^2), the effect sizes (f^2). As mentioned by Sullivan and Feinn [39], while a p -value can inform the reader whether an effect exists, the p -value will not reveal the size of the effect. The results are presented in the Table 4 below.

Table 4: Results of the Hypothesis Testing

Hypothesis	Relationship	Std.Beta	Standard Deviation (STDEV)	T Statistics	P values	Decision	2.50%	97.50%	VIF	R2	Q2	F2
H2	PEU-> SaaS Adoption	0.430	0.068	6.361	0.000	Supported	0.301	0.565	1.375			0.387
H1	PEU-> PENJO	0.185	0.078	2.370	0.018	Supported	0.026	0.333	0.032	0.201	0.111	0.032
H5	PENJO -> SaaS Adoption	0.306	0.064	4.809	0.000	Supported	0.184	0.437	1.252	0.652	0.345	0.215
H4	PU -> SaaS Adoption	0.289	0.073	3.935	0.000	Supported	0.148	0.436	1.466			0.164
H3	PU -> PENJO	0.326	0.078	4.195	0.000	Supported	0.168	0.472	1.332			0.100
H6	PEU-> PENJO -> SaaS Adoption	0.057	0.027	2.060	0.039	Supported	0.011	0.121				
H7	PU -> PENJO -> SaaS Adoption	0.100	0.034	2.945	0.003	Supported	0.046	0.180				

From the above table, it can be concluded that the Perceived Ease of Use ($\beta = 0.185, t = 2.370, p < 0.05, f^2 = 0.032$) and Perceived Usefulness ($\beta = 0.326, t = 4.195, p < 0.01, f^2 = 0.100$) positively influenced perceived enjoyment explaining 20.1% of the variance in enjoyment and thus, H1 and H3 is supported. When examining the predictive effects on the SaaS adoption, Perceived usefulness ($\beta = 0.289, t = 3.935, p < 0.01, f^2 = 0.164$), Perceived Ease of Use ($\beta = 0.430, t = 6.361, p < 0.01, f^2 = 0.387$), and Perceived Enjoyment ($\beta = 0.306, t = 4.809, p < 0.01, f^2 = 0.215$) were significant and thus, H2, H4, and H5 are supported.

Further, when examining the mediation effects on SaaS adoption, Perceived Enjoyment mediates the Perceived Ease of use to SaaS adoption ($\beta = 0.057, t = 2.060, p < 0.05$) and Perceived Enjoyment mediates Perceived Usefulness to SaaS adoption ($\beta = 0.100, t = 2.945, p < 0.05$), and thus, H6 and H7 are supported. When examining the Q^2 results as the model's predictive accuracy using blindfolding procedure, Q^2 results were 0.111 and 0.345 for the two endogenous variables (Perceived Enjoyment and SaaS adoption) respectively indicating that the path model's predictive accuracy is acceptable since the Q^2 values are larger than zero as the rule of thumb.

Discussion and Conclusion

This research was able to determine the factors that influence the SaaS adoption by the undergraduates in the state universities in the North and Eastern part of Sri Lanka and the present status of the SaaS adoption by the undergraduates were also assessed. Further, an extension to the TAM by adding perceived enjoyment in the context of SaaS adoption was tested and the results shows that both perceived usefulness and perceived ease of use predicting perceived enjoyment and the finding is in line with the findings in the earlier researches done by Hsu et al. [14], Wambaa et al. [15] and Hong et al. [16]. Hence, it is confirmed that perceived ease of use and usefulness of SaaS cloud services are important factors in inducing perceived enjoyment and the SaaS that is easy to use and more useful to a user will be an enjoyable experience to the users in using the SaaS services.

Perceived usefulness, Perceived ease of use and perceived enjoyment predicted the SaaS adoption and it aligns with the findings of other researchers like Muthu et al. [17] in e-licensing technology adoption, Hsu et al. [14] in e-book adoption, Wambaa et al. [14] is social network adoption, Hong et al. [16] and Chuah et al. [19] in smartwatch adoption and Alzahrani et al. [26] in online playing context. Previous literature also provides support to the idea that a system or technology that is more useful and enjoyable, the more adoption of the system and thus SaaS. Moreover, perceived enjoyment mediated the variables perceived ease of use and perceived usefulness to SaaS adoption significantly. The researcher was able to model using SaaS adoption as dependent variable

instead of intention which was used mostly in the technology adoption studies as a contribution in response to previous criticism that most researchers stop at intention to use and the intention to use does not necessarily leads to SaaS adoption. Finally, this research would be a guide to apply Confirmatory Factor Analysis using Consistent PLS [40, 41] for empirical research purpose as a model testing analysis.

References

- [1]. 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.
- [2]. Marín, M., Camara, J. M. B., Minguela-Rata, S., & Beatriz. (2017). Environment determinants in business adoption of Cloud Computing. *Industrial Management & Data Systems*, (117), 1-19. doi: 10.1108/IMDS-11-2015-0468
- [3]. Internet World Stats (2017). Internet Users in Asia 2017. Available: <http://www.internetworldstats.com/stats3.htm> (Accessed 5 November 2017)
- [4]. A. Bhattacharjee and S. C. Park, "Why end-users move to the cloud: a migration-theoretic analysis," *European Journal of Information Systems*, vol. 23, no. 3, pp. 357–372, 2014.
- [5]. A. Giessmann and K. Stanoevska, "Platform as a service: a conjoint study on consumers' preferences," in *Proceedings of the International Conference on Information Systems*, (ICIS'12), pp. 2800–2819, Orlando, Fla, USA, December 2012.
- [6] T. S. Behrend, E. N. Wiebe, J. E. London, and E. C. Johnson, "Cloud computing adoption and usage in community colleges," *Behaviour and Information Technology*, vol. 30, no. 2, pp. 231–240, 2011.
- [7]. Y. Wu, C. G. Cegielski, B. T. Hazen, and D. J. Hall, "Cloud computing in support of supply chain information system infrastructure: Understanding when to go to the cloud," *Journal of Supply Chain Management*, vol. 49, no. 3, pp. 25–41, 2013.
- [8]. Burda, Daniel & Teuteberg, Frank. (2014). Understanding the benefit structure of cloud storage as a means of personal archiving - A choice-based conjoint analysis. *ECIS 2014 Proceedings - 22nd European Conference on Information Systems*.
- [9]. Bagozzi, R. P., Davis, F. D., Warshaw, P. R. (1992). Development and test of a theory of technological learning and SaaS adoption. *Human Relations*, 45(7), 660-686.
- [10]. Venkatesh, Viswanath & Morris, Michael & Davis, Gordon & Davis, Fred. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*. 27. 425-478. 10.2307/30036540.
- [11]. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease Of Use, And User Acceptance Of Information Technology. *MIS Quarterly* 13(3), 319–340.

- [12]. 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.
- [13]. , R., & Rothschild, M. (1975). On the allocation of effort. *Journal of Economic Theory*, 10, 358-376.
- [14]. 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>
- [15]. 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.
- [16]. 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
- [17]. 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 ELicensing. *Telematics and Informatics*, 33(4), 925–935.
- [18]. Norazah M. S., Ramayah, T., & Ly, K. K. (2012). Empirical Investigation on Factors Influencing the Behavioral Intention to Use SaaS. *Universal Access in the Information Society Journal*, 11(2), 223-231.
- [19]. 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
- [20]. 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.
- [21]. Igbaria, Magid & Guimaraes, Tor & Davis, Gordon. (1995). Testing the Determinants of Microcomputer Usage via a Structural Equation Model. *J. of Management Information Systems*. 11. 87-114. 10.1080/07421222.1995.11518061.
- [22]. Igbaria, Magid; Parasuraman, Saroh; and Badawy, Michael. 1994. "Work Experiences, Job Involvement, and Quality of Work Life Among Information Systems Personnel," *MIS Quarterly*, (18: 2).
- [23]. Caroll, J. M., & Thomas, J. C. (1988). Fun. *SIGCHI Bulletin*, 19, 21-24.
- [24]. Malone, T. W. (1981). Toward a theory of intrinsically motivating instruction. *Cognitive Science*, 4, 349-361
- [25]. Teo, T. S. H. (2001). Demographic and motivational variables associated with Internet SaaS adoption activities, *Internet Research: Electronic Networking Applications and Policy*, 11(2), 125-137.
- [26]. 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.
- [27]. 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.
- [28]. 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
- [29]. Ringle, C.M., Wende, S., & Becker, J.-M. (2015). "SmartPLS 3," www.smartpls.com
- [30]. 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.
- [31]. Rahman, S. A., Amran, A., Ahmad, N. H., & Taghizadeh, S. K. (2016). Enhancing the wellbeing of base of the pyramid entrepreneurs through business success: the role of private organizations. *Social Indicators Research*, 127(1), 195-216.
- [32]. 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.
- [33]. Rahman, S. A., Amran, A., Ahmad, N. H., & Taghizadeh, S. K. (2015). Supporting entrepreneurial business success at the base of pyramid through entrepreneurial competencies. *Management Decision*, 53(6), 1203-1223.
- [34]. 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.
- [35]. 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.
- [36]. Henseler, Jörg & Hubona, Geoffrey & Ray, Pauline. (2016). Using PLS Path Modeling in New Technology Research: Updated Guidelines. *Industrial Management & Data Systems*. 116. 2-20. 10.1108/IMDS-09-2015-0382.
- [37]. Hu, L.-T., & Bentler, P. M. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychological Methods*, 3(4), 424-453.
- [38]. Bentler, P. M., & Bonett, D. G. (1980). Significance Tests and Goodness-of-Fit in the Analysis of Covariance Structures. *Psychological Bulletin*, 88, 588-600.
- [39]. 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.
- [40]. Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, 81(1), 10-23.
- [41]. Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modelling. *MIS Quarterly*, 39(2), 297-316.