Journal of Information Systems & Information Technology (JISIT) *Vol. 3 No. 1 2018*
ISSN: 2478-0677 *1-11*

Undergraduates' Intention to Use Cloud Computing Services for Academic Purposes

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Abstract. The paper presents to analyse behavioural intention of undergraduates to use cloud computing services for academic purposes at South Eastern University of Sri Lanka. This study was used Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT) which analysed that the constructs of UTAUT including performance expectancy (PE), effort expectancy (EE), social influences (SI), and facilitating conditions (FC), are strong predictors to, or have positively influence on behavioural intention to use cloud computing services for academic purposes among the undergraduate students. However, moderators of UTAUT model are excluded for this study. The UTAUT constructs for this study are used and analysed using structural equation modelling (SEM) through partial least squares path modelling (PLS-SEM). Survey questionnaire through Google Forms shareable link was distributed to 394 participants. 23 responses out of 394 responses are rejected because of insufficient answers. SmartPLS 3 software was used for analysing the data. The path coefficient (β) of PE, EE, SI, and FC are 0.27, 0.279, 0.181, and 0.196 respectively. Therefore, findings of this study concluded that there are significant positive effects of the constructs (PE, EE, SI and FC) on behavioural intention to use cloud computing services among undergraduate students at South Eastern University of Sri Lanka.

Keywords: Cloud Computing Services, Unified theory of acceptance and use of technology, Undergraduate students' Intention, South Eastern University of Sri Lanka.

1 Introduction

Nowadays, cloud computing is a trending term to all over the world and is used for storing, backing up, recovering and sharing purpose among organization, universities and other related institution for various purposes. It has become a collaborative technology among people. To contact business, cloud computing services, or the use of internet-based technologies is recognised as an important area for IT innovation and investment (Goscinski et al,.2010; Armbrust et al., 2010; Ercan, 2010). Particularly, University students obtain several benefits from using cloud computing services by increasing performance of computer and capacity of storage.

Cloud computing provides many facilities to learn and share the things among students. As a perspective of technology, cloud computing services establishes pool and footnote of learning materials, association of knowledge in a beneficial way, gathering, and discovery of worthwhile learning materials from the space of knowledge, and distribution of engaged and personalized learning materials. (Apalla, Kuthadi, & Marwala, 2017, p. 1011).

In education sector research on cloud computing services has been well investigated. However, research on cloud computing services at SEUSL among undergraduates is scarcely investigated. Nowadays, Plenty of students in the university use cloud computing services for academic purposes. Therefore, this study aims to explore the behavioural intention to use cloud computing for academic purpose among undergraduate students at SEUSL.

2 Literature Review

Cloud computing is a technology services which provide applications, storage, backup and servers via internet and capability for accessing data from everywhere at any time. The Cloud computing technology influence on everyone's day to day life by using a variety of brand names such as Google Drive, OneDrive, Dropbox and Apple's iCloud. The Cloud computing services technology plays a vital role in business sector and now is adopted in education sector.

A clear definition of cloud computing is provided by the US National Institute of Standards and Technology (NIST) as "*a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction*" (Mell & Grance, 2011:2).

According to the National Institute of Standards and Technology (NIST) (Simmon, 2018), Cloud computing holds three main services which are Software as a Service (SaaS)**,** Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). In Software as a Service (SaaS), Users do not need to install and run software on their devices but can use on variable devices (Simmon, 2018, p. 9). Simmon explained that SaaS provider is available for deploying, configuring, maintaining, and updating the operation of software (p. 9). PaaS offers environments and techniques for developing software containing personalization and integration tools and works remotely with existing or other programs presented (Alam, 2013). IaaS cloud technology provides required resources from users including computing resources, network resources and storage resources (Simmon, 2018, p. 11). Cloud deployment model was developed and divided as four various categories by NIST. Those categories are private cloud, community cloud, public cloud, and hybrid cloud.

- **Private Cloud -** The private cloud is exclusively accessible for single customer or organization. It can be belonged to, managed, and controlled by a single organization, a third party, or some combination of them (Simmon, 2018).
- **Community Cloud -** Community Clouds are developed or operated by a specific community of organizations or people to collaborate their common interests, such as missions, security requirements, policy, and compliance considerations (Simmon, 2018).
- **Public cloud -** Public cloud is used by general public or large enterprises and may be owned, managed, and controlled by a business, academic, or government organization, or some combination of them (Simmon, 2018).
- **Hybrid cloud -** Hybrid cloud contains combination of two or more different cloud infrastructure such as private, community or public. Two or more clouds are merged together by standardized or proprietary technology (Simmon, 2018) to grant maximum benefits and cost reductions.

Several studies were developed by using the UTAUT model on various industries such as healthcare, business, information systems, education, and banking. However, plenty of studies was conducted the UTAUT model to explore in education sector for analysing intention and actual use of technology among teachers, students and other related staffs. Venkatesh (2013) explained that the UTAUT gives a holistic model to obtain people's behaviour or attitudes and intentions to adopt cloud computing solutions (p. 63). To analyse the UTAUT model, 430 respondents are selected but only 42% of responses was completely answered in the survey. With 5 predictors and a response probability of 0.05, the effect size was 0.15 (p. 15). Venkatesh indicated that no certain tests for validity were explored because the instrument scales were depended on both TAM and UTAUT models which were proven reliable and valid earlier (p. 87). Findings of the study concluded that strong predictors of trust and the reliability in cloud computing providers were perceived use (PU) and perceived ease of use (PEOU). UTAUT variables which are Performance expectancy, effort expectancy, social influence, and facilitating conditions, were strong predictors of behavioural intentions.

According to Paquet's (2013) quantitative study, information delivered about consumer perceptions on the level of security in cloud computing if security is the important deterrent for adoption of cloud computing (p. 1). The study was conducted to identify security areas which was depend on security concerns from IBM information security capability reference model (p. 1). Perceived usefulness was a strong predictor for use of cloud computing in the findings of Paquet's (2013) study. Paquet reviewed that adoption of cloud computing increases when perceived ease of use increases (p. 102).

Alqallaf's (2016) study aimed to explore perceptions of Kuwaiti mathematical elementary teachers towards their ability to use mobile learning or m-learning and to determine the restrictions that could demotivate them from it. Theoretical frameworks of the study were Constructivism and Technological Pedagogical Content Knowledge (TPACK). Findings of the study revealed that budget constraints, IT limitations, time constraints, and administrative support was taken as influencing factors that influenced teachers' use or non-use of cloud computing. Alqallaf justified that there was a disconnection between perception of teachers about cloud computing and support offered from their schools, districts, or the ministry of education.

By using consumers' age, gender and education in a correlation research study which was conducted by Joglekar (2014) were explored in relevance to adopt cloud computing technologies. The theoretical framework of the study was contributed by Davis' (1989) TAM model. However, the impact of gender and age towards the independent variables were not explored. The researcher failed to measure different marketing materials that organization implement to target their consumers, and which is taken as one of limitation of the study. Marketing generally differs based on age, gender, and education of the target population. Joglekar's (2014) study has low strength of evidence.

Dawson's (2015) correlational quantitative study was conducted by using TAM model to determine attitudes towards technology and to detect the reasons why individuals choose to operate special technologies. Findings of the study explained that decision makers of IT in higher education established significant levels of perceived usefulness, perceived ease of use, perceived security, perceived reliability, perceived benefits (p. 92) which stated positive level of perception towards technology influenced decisions of participants to adopt to cloud computing for their institutions. The study used extremely thorough methods to define reliability and validity measures and provided precise review of literature which will be used for future studies. However, the research related to behavioural intention to use certain technology are scarcely investigated among students of South Eastern University of Sri Lanka which reason behind to be established this study.

3 Theoretical Framework

This study is established to explore the significant influences of independent variables of UTAUT which are Performance expectancy, effort expectancy, social influence, and facilitating conditions, on dependent variable of UTAUT which is Behavioural Intention to use cloud computing services for academic purposes.

- **Performance Expectancy -** the fundamental to which persons perceive that using a technology enhance or create an impact positively their “Job Performance” (Venkatesh *et al*., 2003).
- **Effort Expectancy -** an extent to which individual perceives that using technology as easily (Venkatesh *et al*., 2003).
- **Social Influences** - the extent to which an individual believes to use technology based on others’ usage of technology. (Venkatesh *et al*., 2003).
- **Facilitating Conditions** - the extent to which persons determine to use technology based on availability of its “technical and organization infrastructures” (Venkatesh *et al*., 2003).
- **Behavioural intention (BI) -** the degree to which a person decides to use certain technology in future purpose (Venkatesh *et al*., 2003).

Venkatesh et al.’ (2003) UTAUT constructs are triggered by moderating factors which are Gender, Age, Experience, and Voluntariness of Use. This study excluded all moderators of UTAUT constructs. Furthermore, Venkatesh et al.’s (2003) UTAUT contains Use Behaviour (UB) as a factor of adoption of the technology. Use Behaviour (UB) refers actual use and adoption for technology use. UB is a self-reported psychological factor and did not include in this study. The research hypotheses are shown following:

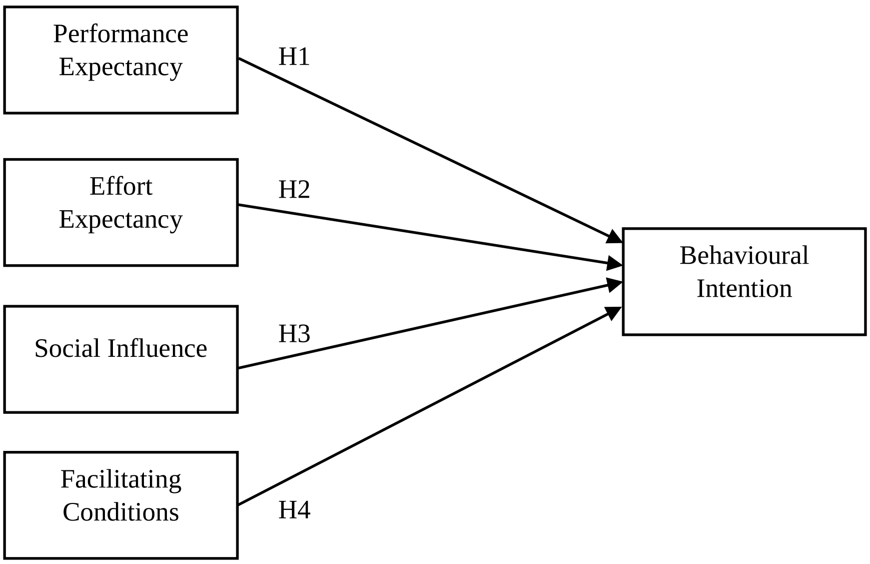

Fig. 1. Conceptual framework

- **H1:** Performance expectancy will positively impact on undergraduate students' Behavioural Intention to use cloud computing services for academic purposes.
- **H2:** Effort expectancy will positively impact on undergraduate students' Behavioural Intention to use cloud computing services for academic purposes.
- **H3:** Social Influences will positively impact on undergraduate students' Behavioural Intention to use cloud computing services for academic purposes.
- **H4:** Facilitating conditions will positively impact on undergraduate students' Behavioural Intention to use cloud computing services for academic purposes.

From above stated hypotheses, the conceptual framework is established as illustrated in fig. 1.

4 Methodology

The population of this quantitative study include the undergraduate students of South Eastern University of Sri Lanka who use or do not use cloud computing services for academic purposes. Specific groups and types of students were excluded for sampling frame. Because, technologies are adopted to students without any certain groups or types. 5153 Undergraduates including 1633 males and 3620 females are following degrees at South Eastern University of Sri Lanka. This study conducted 371 sample students from all faculties of South Eastern University of Sri Lanka by using convenience sampling methods. The survey questionnaire is sent to 394 respondents. But some of them did not answer some questions. 5% of 394 responses or 23 responses are considered as missing data. Finally, polished respondents who provide answers completely are 371 which meets sample size of this study. For this study, Smart PLS 3 Software was used for testing hypotheses regarding to this study.

Smart-PLS has slighter size of requirements than CB-SEM (Henseler, Ringle, and Sinkovics, 2009). Therefore, PLS-SEM was selected for this study. PLS-SEM accesses a sample size ten times bigger than the largest predictor (Hair et al., 2014). This study sample size would be small or using CB-SEM. According to Jöreskog and Wold sited by Henseler, Ringle, and Sinkovics 2009, PLS-SEM would be proposed in cases in which high complexity and a low extent of theoretical information are obtainable.

5 Data analysis and Findings

According to Bollen (1989) cited by Hair et al. (2012), Structural Equation Modelling (SEM) has been used by researchers for analysing their hypotheses, theories and concepts for management and marketing research studies. Partial Least Squares based Structural Equation Modelling (PLS-SEM) and Covariance-based Structural Equation Modelling (CB-SEM) are famous modelling nowadays for data analysis methods for scholars. This study is used PLS-SEM model which contains the measurement model (outer model) and structural model (inner model) for testing hypotheses to answer the research questions.

5.1 Measurement Model Analysis

Measurement model typically analyses the observed variables related to their latent variable (outer model). Reliability of measurement model generates internal consistency reliability and indicator reliability. Validity consists of convergent validity and discriminant validity (Henseler et al., 2009). Internal consistency is generated from Cronbach's alpha tests and Composite reliability. Cronbach's alpha tests calculates the internal consistency for this study as proposed by Laerd Statistics (2015). Cronbach's alpha values should be higher than 0.7 which indicates the reliability of variables (Field, 2009). According to table 1, all variables are higher than 0.7 after eliminating EE6 question and SI5 question because of low factor loadings. The Composite reliability calculates whether all indicators manipulate the similar outer loading (latent variables) and relies on zero to one. For this study, table 1 illustrated the composite reliability (CR) value of variables are above 0.7 according to Hair et al. (2014).

For analysing the individual indicator reliability, the factor loading of measurement items or variables relied on latent variable should be examined to prove that the variance generated from each measurement item related with a specific latent variable is larger than the variance generated by other measurement items related with another latent variable. According to Henseler et al. (2009), table 1 shows that all items of UTAUT variables contain the loading above 0.4.

Convergent validity measures the degree of correlation between those instruments which are expected to be 'theoretically' relevant with each other. Convergent validity is generated by measuring the Average Variance Extracted (AVE) which represents the proportion of the detailed variance. Minimum amount of 0.5 is accepted as AVE ranges 0 to 1 (Fornell and Larcker, 1981; Henseler et al., 2009). According to this table 1 explained that all variables contain the amount which is obtained above 0.5.

Table 1. Measurement Model of the results

Variables	Items	Loading	Cronbach's Alpha	AVE	CR	Rho_A
Behavioural Intention	BI1	0.852	0.858	0.779	0.913	0.862
	BI2	0.92				
	BI3	0.875				
Performance Expectancy	PE1	0.641	0.881	0.631	0.911	0.887
	PE2	0.771				
	PE3	0.838				
	PE4	0.83				
	PE5	0.848				
	PE6	0.819				
Effort Efficiency	EE1	0.799	0.898	0.711	0.925	0.9
	EE2	0.877				
	EE3	0.857				
	EE4	0.809				
	EE5	0.872				
Social Influence	SI1	0.873	0.886	0.746	0.922	0.888
	SI2	0.851				
	SI3	0.895				
	SI4	0.834				
Facilitating Conditions	FC1	0.748	0.754	0.579	0.845	0.776
	FC2	0.845				
	FC3	0.63				
	FC4	0.803				

Table 2. Discriminant Validity (Fornell-Larcker-Criterion)

	Behavioural Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence
Behavioural Intention	**0.883**				
Effort Expectancy	0.645	**0.843**			
Facilitating Conditions	0.572	0.564	**0.761**		
Performance Expectancy	0.618	0.633	0.511	**0.795**	
Social Influence	0.505	0.466	0.449	0.394	**0.864**

Discriminant validity measures the level of correlation between measurement items of one construct with measurement items of other unrelated construct(s), which should not be correlated with others theoretically. The Fornell-Larcker-Criterion and cross-loading are the ways to tests discriminant validity in which the former is applied on the construct level while the latter is applied on the indicator (measurement item) level (Henseler et al., 2009).

Table 3. Indicator Item cross-loading

	Behavioural Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence
BI1	**0.852**	0.515	0.455	0.519	0.459
BI2	**0.92**	0.615	0.555	0.553	0.473
BI3	**0.875**	0.572	0.501	0.563	0.406
BI4	0.491	**0.799**	0.462	0.531	0.346
EE1	0.559	**0.877**	0.513	0.54	0.347
EE2	0.545	**0.857**	0.448	0.547	0.401
EE3	0.573	**0.809**	0.476	0.514	0.41
EE4	0.543	**0.872**	0.476	0.537	0.456
EE5	0.359	0.312	**0.748**	0.38	0.344
FC1	0.519	0.508	**0.845**	0.477	0.334
FC2	0.378	0.452	**0.63**	0.323	0.373
FC3	0.459	0.424	**0.803**	0.359	0.332
FC4	0.435	0.426	0.409	**0.641**	0.403
PE1	0.434	0.422	0.372	**0.771**	0.357
PE2	0.507	0.519	0.395	**0.838**	0.275
PE3	0.531	0.538	0.441	**0.83**	0.343
PE4	0.507	0.544	0.435	**0.848**	0.286
PE5	0.517	0.549	0.381	**0.819**	0.237
PE6	0.455	0.404	0.423	0.353	**0.873**
SI1	0.447	0.43	0.414	0.362	**0.851**
SI2	0.437	0.41	0.371	0.344	**0.895**
SI3	0.403	0.363	0.339	0.298	**0.834**
SI4	**0.852**	0.515	0.455	0.519	0.459

Table 4. Discriminant Validity (HTMT)

	Behavioural Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence
Behavioural Intention					
Effort Expectancy	0.732				
Facilitating Conditions	0.701	0.679			
Performance Expectancy	0.71	0.71	0.624		
Social Influence	0.579	0.521	0.556	0.451	

Square roots of Average Variance Extracted (AVEs) are written in bold at table 2 and higher than all other variable related row and column (Fornell & Larcker, 1981). Moreover, all variables' individual items are illustrated in table 3 for analysing cross-loading and represented that certain items are higher in their related construct compared to other items. Moreover, there is an additional new approach to calculate the discriminant validity that is heterotrait-monotrait ratio of correlations (HTMT) in variance-based SEM. Table 4 shows the HTMT value which indicates that correlation between each construct are not adequate because it contains the value less than 0.85. Therefore, this study has met the discriminant validity by determining Fornell-Larcker-Criterion, cross-loading and HTMT ratio.

Table 5. Collinearity statistics (VIF in outer model)

	VIF
BI1	1.972
BI2	2.75
BI3	2.176
BI4	2.77
EE1	2
EE2	3.034
EE3	2.466
EE4	1.993
EE5	2.936
FC1	1.56
FC2	1.801
FC3	1.197
FC4	1.601
PE1	1.47
PE2	2.057
PE3	2.396
PE4	2.258
PE5	2.932
PE6	2.64
SI1	2.387
SI2	2.21
SI3	2.901
SI4	2.22

Table 6. Collinearity statistics (VIF in inner model)

	BI
EE	2.014
FC	1.641
PE	1.786
SI	1.376

Multicollinearity tests variance inflation factor (VIF) which should be higher than 4.0 (some scholars use the more lenient cut-off of 5.0) and less than 0.25 (someone uses the more lenient cut-off of 0.2) value. According to Hair *et al*. (2011), the tolerance value of 0.2 or lower than and a VIF value of 5 and above are used for this study for analysing collinearity problem. Table 5 and shows multicollinearity of inner and outer model which shows all VIF value below 5 (Hair *et al*., 2011).

5.2 Structural Model Analysis

In PLS-SEM, structural model contains path coefficient to measure the significant of structural model path correlations, the explained variance (R^2) value to measure the predictive of model accuracy, the Prediction Relevance **(**Q^2) value to measure predictive relevance of model and the effect size (f^2) to measure the substantial impact of independent variable (exogenous) on the dependent variable (endogenous) (Hair et al., 2013).
The path coefficient (β) tests the path relationships among variables and ranges from -1 to +1 (Hair et al., 1998) and t-Value which is measured from 1000 samples of bootstrap technique, should be higher than 1.96 at significant level 0.05 (Hair et al., 2014). Table 7 shows significant path coefficients and t-values of all variables. The coefficient of determination indicates the proportion of the variance in every predicted (endogenous) variable that can be interpreted. The coefficient reflects by the squared multiple correlation (R^2) as in simple regression. Below illustrated table 7 shows the 0.550 (55.0%) of variance in behavioural intention throughout the other variables to use cloud computing services.

Table 7. The results of structural model

Path	Path Coefficient	t-Value	Decisions	R^2	f^2	(Q^2)
PE -> BI	0.27	4.357*	Supported	0.550	0.091	0.044
EE -> BI	0.279	3.049*	Supported	0.550	0.086	0.044
SI -> BI	0.181	3.822*	Supported	0.550	0.053	0.023
FC -> BI	0.196	4.379*	Supported	0.550	0.052	0.026

The F-test is utilised to describe the strength of the moderating effect size (f^2) by including or excluding a construct to an earlier tested model and evaluating the change in the explained variance R^2 of ultimate endogenous latent dependent variable (Henseler *et al*., 2009; Henseler and Fassott, 2010). All values of f^2 are given at moderate level which means that all variables have that moderate effect size (shown in Table 7) according to Henseler *et al*. (2009).

The Predication Relevance (Q^2) also known as the Stone-Geisser's Q^2 test (Geisser, 1974; Stone, 1974) represents the ability of model to evaluate the measurement items of any endogenous latent variable in the model (Henseler *et al.*, 2009). According to Henseler *et al.*

(2009) and Urbach and Ahlemann (2010), performance expectancy, effort expectancy, and facilitating conditions are at medium level predictive relevance while social influences is at small predictive relevance. However, all Q2 are above zero. Therefore, this model has predictive relevance.

6 CONCLUSION

Findings of this study explained that undergraduate students' intention in South Eastern University of Sri Lanka to integrate new system or technology by utilizing a model that has confirmed to possess high reliability and validity through this study survey questionnaire. The UTAUT model are used for this study and which provides effective results. Stated hypotheses for this study are accepted because it has significant impact of the exogenous on endogenous variables. From PLS-SEM analysis, path coefficient of PE, EE, SI and FC on BI shows positive significant effects. This study furtherly will support future scholars for conducting future analysis regarding to cloud computing services. This study also helps to move to adopt the use of cloud computing services among undergraduates' students for academic purposes.

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