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Influencing Factors on Student's Willingness to Embrace Cloud Computing: An Empirical Study in Sri Lanka

L. I. S. Kaluarachchi[1*], H. P. Diunugala[2], B. H. Senevirathna[3], N.A.N.J. Maduwansha[4] T. S. N. D. Kumarage[5], and K. A. P. J. P. Gunawardhana[6]

[1,2,3,4 and 5]Department of Social Statistics, University of Sri Jayewardenepura, Sri Lanka, [6]Western Sydney University, Australia.

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*Corresponding author
E-mail address:
liskaluarachchi.tmp@sjp.ac.lk

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ABSTRACT

Cloud computing is an important factor in the realm of information technology; however, its adoption by individual users and students remains insufficient. This paper examines the elements that affect students' intention to use cloud services, addressing a gap in the literature that predominantly focuses on business customers. A structured questionnaire was given to 347 respondents in order to test a model based on the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). Descriptive analysis, principal component analysis, and Structural Equation Modeling (SEM) were employed to infer the results. The findings indicate that perceived usefulness, perceived behavioral control, subjective norms, and attitudes toward cloud computing all exert a direct influence on students' intention to utilize cloud computing. It was found that behavioral intention was indirectly influenced by perceived ease of use, perceived transferability of computer skills, and trust in cloud computing providers. Additionally, perceived risk was directly affected by concerns related to vendor lock-in and security. Attitudes toward cloud computing were directly shaped by perceived usefulness, which, in turn, was indirectly influenced by ease of use, transferability of computer skills, and trust in providers. Furthermore, the results suggest that perceived usefulness acted as a fully mediating variable, whereas attitudes toward cloud computing served as only a partial mediator. As policy implications, the paper suggests that academic policies should enhance students' intention to adopt cloud services by emphasizing the practical benefits of cloud computing, enhancing user-friendliness, promoting digital literacy, ensuring data security and transparency, and fostering positive attitudes toward cloud technologies.

1. Introduction

Computers are now a necessary component of our everyday life, having completely changed the way we work and live. As technology continues to advance rapidly numerous countries are investing in computer-based education to prepare the future workforce (Zamani, 2014). However, prior to 2006, challenges in data storage necessitated storing critical personal data on traditional media, such as local hard drives, external hard drives, pen drives, or CDs/DVDs, posing significant risks to data safety. Cloud storage solutions effectively address this issue, with their demand and proliferation increasing rapidly. The concept of cloud computing has a long history dating back to the 1960s when John McCarthy first proposed it (Bairagi & Bang, 2015). However, it wasn't until the launch of Amazon Web Services (AWS) in 2006 marked the point at which cloud computing gained widespread popularity. Other major technology companies, such as Google and IBM, also began offering cloud computing services around the same time. The National Institute of Standards and Technology (NIST) defines cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources," which can be rapidly provisioned and released with minimal management effort (Mell & Grance, 2011). Cloud computing essentially provides a virtual face for traditional data centers, allowing users to access a wide range of computing resources from anywhere, at any time, through the internet.

Cloud computing appears to enable the provision of computer services via the Internet on-demand from remote locations, potentially making the physical location of computers and data storage independent of each other (Wyld, 2010). Cloud computing offers many benefits, such as reducing the maintenance and power consumption of computers, lowering storage device costs, enabling collaboration, and being an eco-friendly system. Cloud service providers provide a variety of services, including data analytics, databases, developer tools, management tools, security and identity, storage, and machine learning (Buyya et al., 2009). Users can access cloud services on-demand. Furthermore, users pay for services as they are utilized, with some services offered for free. During this study period, the Covid 19 pandemic spread throughout the world, and traditional server methods provided less support during this period due to lockdowns. All academic operations were significantly supported by cloud storage. Devices such as laptops, tablets, mobile phones, and workstations could seamlessly connect to the cloud network, and instructors and students can access cloud computers from anywhere. Using cloud computing does not require students or professors to physically visit a classroom, as it does in traditional learning methods, and students and teachers may attend lectures from anywhere.

Various explanations may be observed from the perspective of the educational institution. As cited by Ghanem (2019), according to Hussein and Khalid (2016), In accordance with the demands of society in the information technology era, one of the key goals of education is to prepare individuals for this evolving landscape. It is essential to integrate and guide education through the effective use of technology. Moreover, most educational institutions place a higher priority on research and learning than on the installation of advanced IT infrastructure. This is primarily due to the high cost of IT infrastructure. According to (Zamani, 2014), cloud computing ultimately improves quality, broadens access to educational resources, and offers significant cost savings. There are many advantages of using cloud computing. Users can access their workspace at any time, with services available on demand. Cloud computing is environmentally friendly, capable of handling massive amounts of data, and eliminates the need to back up everything to a USB device or external hard drive. It also overcomes geographical barriers, offering significant advantages. Numerous studies have identified various factors influencing university students' intention to use cloud computing. Key variables include perceived ease of use, perceived usefulness, and perceived security. In addition, many theories were used in past research. Despite all the advantages cloud computing offers, developing trust in cloud service providers is an important step toward effective adoption of cloud-based systems, and risks—like privacy and security issues—need to be minimized (Buyya et al., 2009). Even though various studies have focused on cloud computing from a technical viewpoint, such as virtualization and security, the key barrier to adopting cloud computing often involves perceptions or attitudes rather than technical constraints (Bogataj Habjan & Pucihar, 2017; Marston et al., 2009). Furthermore, Li & Chang (2012a) mentioned that the lack of awareness about cloud computing is one of the main barriers to its adoption. In the context of the higher education sector, many students are hesitant to adopt cloud computing due to security and skill concerns related to cloud technology (Li & Chang 2012a). The COVID-19 pandemic has highlighted the critical role of cloud computing in supporting online education within higher education. As educational institutions worldwide were forced to close, online education emerged as the sole viable option. However, understanding university students' behavioral intentions towards adopting cloud computing remains a crucial issue.

Studying university students' attitudes and perceptions towards cloud computing environments is crucial. According to the (Buyya et al., 2009), the term 'Cloud Computing Environment' typically refers to the comprehensive ecosystem or infrastructure that supports cloud computing services. It is important to consider aspects such as perceived usefulness (PU), perceived ease of use (PEoU), perceived risk (PR), trust (TR), attitudes toward cloud computing (ATC), perceived behavioral control (PBC), subjective norms (SN), perceived provider reputation (PRP), and perceived transferability of computer skills (PTS) in establishing an explanation of the BI of university students for adopting cloud computing. Existing research has often focused on technical aspects and barriers, there is limited exploration into these psychological, social, and perceptual factors that are critical in shaping students' decisions regarding cloud technology adoption. Although earlier research has identified the technical viability and security issues related to cloud computing (Buyya et al., 2009; Marston et al., 2009), less inquiry has been conducted into how aspects such as trust in service providers, perceived risks, and subjective norms impact the adoption behaviors of students in higher education. Moreover, the shift to online education during the COVID-19 pandemic has underscored the urgency of understanding these factors, as universities increasingly rely on cloud-based platforms for remote learning. This study has three primary objectives. Firstly, the research investigates factors' influence on perceived risk in cloud computing adoption among undergraduates. Secondly, the study examines how these factors shape attitudes towards adopting cloud computing. Ultimately, the study intends to determine how these suggested factors shape the behavioral intentions of undergraduates toward adopting cloud computing.

Together, these objectives present a more comprehensive understanding of the factors that influence undergraduate students' intentions in the adoption of cloud computing a subject significant for both educational institutions and providers of cloud services.

In the remainder of this study, we present in different sections the materials and methods, results and discussion, conclusions, policy implications, and suggestions for future research.

2. Materials and Methods

The Technology Acceptance Model (TAM), which is well-known for its highly predictive potential in predicting the adoption of various IT systems, is one of the most well-known frameworks for comprehending technology adoption (Lee et al., 2003). TAM states that perceived utility (PU) and perceived ease of use (PEoU) are the two main perceptions that impact user adoption of IT systems (F. D. Davis, 1989). PU represents the user's perception of how much IT can improve their performance at work (F. D. Davis, 1989). In contrast, perceived ease of use (PEoU) is the extent to which a user thinks a new technology would be simple to use (F. D. Davis, 1989).

Attitude is an individual's general assessment of performing a certain behavior. It involves the expected favorable or unfavorable consequences related to the use of cloud applications. Subjective norm represents the perceived social influence or expectations from others important to an individual regarding the decision to perform or not to perform a behavior is influenced by behavioral intentions. Perceived behavioral control, on the other hand, reflects an individual's perception of the ease or difficulty associated with performing a specific task.

Attitude toward cloud applications refers to an individual's general assessment of the expected consequences of adopting the applications. Several researchers have indicated that cloud computing provides numerous advantages, which range from cost reduction and better document compatibility and reliability to universal accessibility of documents. However, the key challenges associated with it include data security and privacy issues and vendor lock-in problem (Miller, 2009). As such, perceptions of cloud computing can be outlined in three main constituents: perceived usefulness, perceived ease of use, and perceived risk. Koehler et al.(2010) assert that the complexity of service offered through cloud computing may vary highly, with some services demanding training for end-users, while others can be so intuitive and hence easy to use. A cost-benefit analysis indicates that individuals tend to prefer cloud applications that offer an experience comparable to traditional desktop or mobile computing environments, as these require minimal training or learning to utilize their features effectively. Regarding the transfer of computer skills to new applications, Li & Chang (2012a) suggest that when new applications share common characteristics with previously learned ones (such as similar graphical user interfaces, functionality, and syntax) the perceived transferability of skills is significantly higher.

Despite the fact that cloud computing has many benefits for users, there are also concerns associated with it, such as concerns related to privacy, security, integrity, availability, user control, vendor lock-in, and performance delays (Sultan, 2010). All these risk variables have an impact on the trustworthiness of a cloud application (or its provider). These risks collectively contribute to an overall assessment of the risk level associated with using cloud applications. From the perspective of the Theory of Planned Behavior (TPB) , such risks reflect users' expectations of negative behavioral outcomes stemming from cloud computing, as well as their evaluation of the severity of these outcomes. Provider reputation, defined as the general belief that a provider will act as promised or anticipated, serves as a key indicator of how effectively a provider mitigates potential risks (Koehler et al., 2010). However, while cloud computing was initially designed to mitigate privacy and security concerns by reducing reliance on physical equipment and leveraging the expertise of experienced providers, it has also introduced a new set of privacy and security challenges. These issues arise particularly when providers fail to adequately protect or respect customer information (Svantesson & Clarke, 2010). As a result, conducting thorough due diligence on providers' security protocols remains essential (Li & Chang (2012b).

This issue pertains to the challenges customers face when transferring data and applications between cloud providers (Koehler et al., 2010). Armbrust et al. (2010) identify data lock-in as one of the ten primary barriers to cloud computing development. They explain that cloud storage systems remain largely proprietary, preventing consumers from seamlessly migrating their data and applications between different providers.

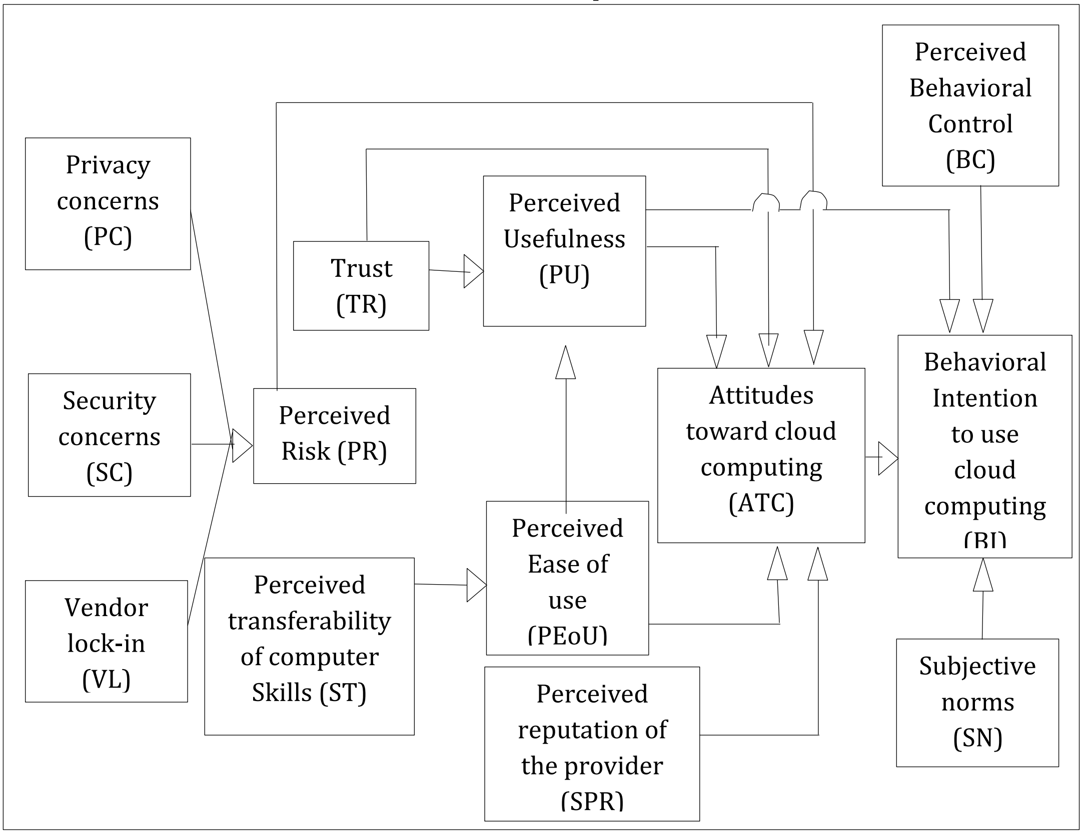

Figure 1. The study's conceptual framework.

This study utilized a quantitative approach using deductive research and hypothesis testing. The purpose of this study was to examine the aspects that affect university students' intentions to use cloud computing. This study employed an explanatory research model with the dependent variable being the behavioral intention to adopt cloud computing, consisting of 13 independent factors Demographic characteristics, including gender, province, academic year, department, proficiency in English and computer skills, as well as experience with computers and cloud computing, were taken into account. This study proposes the following hypotheses to explore factors influencing behavioral intentions towards cloud computing:

First Objective:

Prior research (Li & Chang, 2012) indicates that concerns such as privacy and security issues heighten perceived risk in cloud computing adoption, influencing users' behavioral intentions.

H_1: Perceived concerns positively affect perceived risk.

Studies (Burda & Teuteberg, 2014) have shown that perceived security concerns increase the perceived risk associated with cloud services, potentially discouraging adoption.

H_2: Perceived security concerns positively affect perceived risk.

Vendor lock-in, which refers to the difficulty of switching between cloud providers, amplifies perceived risks (Li & Chang, 2012). Dependence on a single provider heightens users' risk perception, thereby influencing their behavioral intentions.

H_3: Vendor lock-in positively affects perceived risk.

Second Objective:

Higher trust in cloud computing providers reduces perceived risks (Alotaibi, 2014) and fosters positive attitudes toward cloud services, thereby influencing behavioral intentions favorably.

H_4: Trust positively affects attitudes toward cloud computing.

Perceived usefulness is a critical determinant of attitudes towards new technologies (Davis, 1989).

Cloud services perceived as useful are more likely to be positively evaluated and adopted, influencing behavioral intentions.

H_5: Perceived usefulness positively affects attitudes toward cloud computing.

Higher perceived risks associated with cloud computing negatively impact attitudes (Li & Chang, 2012), potentially reducing behavioral intentions.

H_6: Perceived risk positively affects attitudes toward cloud computing.

The perceived reputation of a provider influences perceptions of reliability and trustworthiness (Li & Chang, 2012), enhancing attitudes toward the provider's services and cloud computing in general.

H_7: Perceived reputation of the provider positively affects attitudes toward cloud computing.

Ease of use plays a critical role in technology acceptance (Davis et al., 1989). Cloud services that are perceived as easy to use are more likely to foster positive attitudes, which in turn influence behavioral intentions.

H_8: Perceived ease of use positively affects attitudes toward cloud computing.

Third Objective:

Positive attitudes increase the likelihood of adopting cloud computing services (Alotaibi, 2014), motivating users to align their behaviors with positive perceptions.

H_9: Attitudes toward cloud computing positively affect behavioral intentions to use cloud computing.

Social influences impact adoption decisions (Ajzen, 1991). Positive subjective norms, such as recommendations from peers or faculty, can positively influence behavioral intentions towards cloud computing.

H_{10}: Subjective norms positively affect behavioral intention to use cloud computing.

Perceived control over using cloud services influences behavioral intentions (Li & Chang, 2012), enhancing confidence in adopting cloud computing.

H_{11}: Perceived behavioral control positively affects behavioral intention to use cloud computing.

Perceived usefulness directly influences behavioral intentions (Davis, 1989). Cloud services perceived as useful are more likely to be adopted, reflecting the user value in integrating them into academic activities.

H_{12}: Perceived usefulness has a positive effect on behavioral intention to adopt cloud computing.

The study population was drawn from the Faculty of Humanities and Social Sciences at the University of Sri Jayewardenepura. According to Sri Lankan university statistics, the University of Sri Jayewardenepura has the largest student population in the country which consists of 3,508 students from first year to fourth year, and the sample size was determined to be 346 using the Morgan and Krejcie formula, and 500 students were randomly selected using a simple random sample. Data collection was conducted using an online questionnaire created with Google Forms, which was distributed to the selected students via WhatsApp. Reminder messages were sent every three days to improve response rates. Participants were informed that the study was interested in their views on cloud computing and was instructed to assume a Google Drive if they were unfamiliar with cloud computing.

The questionnaire contained 65 questions, including 11 questions on demographic factors and 53 questions to investigate the 13 suggested factors. The questions were presented in various formats, including multiple-choice questions, checkbox questions, 5-point Likert scale questions, and drop-down selections.

Validity, content, and reliability of the questionnaire was analyzed using a pilot test involving 20 students. Demographic information from the respondents was analyzed using descriptive statistics, while the composite index was developed for analysis through Principal Component Analysis for examining each component in the questionnaire. A two-sample t-test and one-way ANOVA were carried out in examining demographic characteristics that affect an intention to adopt cloud computing. Structural Equation Modeling (SEM) was implemented in establishing the study examining the factors influencing university students' intention to use cloud computing. To ensure the reliability and validity of the study, Cronbach's Alpha, the Kaiser-Meyer-Olkin (KMO) index, Bartlett's test of sphericity, Composite Reliability (CR), and Total Variance Explained were utilized. Additionally, Convergent and Discriminant validities have been investigated further. CB-SEM, that is, covariance-based Structural Equation Model, has been identified as the principal statistical tool employed in the current study.

3. Results and Discussion

3.1 Descriptive Statistical Summary Results

To provide a comprehensive understanding of the demographic composition of the study sample, a detailed descriptive statistical summary is presented.

The study sample consisted mostly of female students, representing 80.69% of the total students. In terms of academic level, the majority were third-year students (27.7%), followed by first-year (26.8%) and second year (23.9%) students. Fourth-year students had the smallest representation (21.6%). The sample included students from all provinces in Sri Lanka, with the Western province having the highest number of students 30.5% (106) and the Northern province having the lowest number of students 0.3% (1). Most of the students had 3-5 years of computer experience (40.06%), while the proportion of students with more than 8 years of computing experience was the lowest (15.56%). Similarly, the majority of students had less than two years of cloud computing experience (45.82%). Regarding cloud service providers, most students were familiar with Google Cloud (40.12%). Knowledge of other service providers such as IBM, Oracle, and Amazon were limited (1.20%, 2%, and 2.60%, respectively). It is worth noting that 34.9% of students were familiar with more than one service provider. When it comes to specific cloud services, most students were familiar with two services (40.60%), while Dropbox, Windows Azure, and Google Compute Engine services were underutilized (1.40%, 1.20%, and 0.60%, respectively).

Cronbach's Alpha, the Kaiser-Meyer-Olkin (KMO) index, Bartlett's test of sphericity, Composite Reliability (CR), and Total Variance Explained are among the reliability and validity measures presented in Table 2..Since all the Cronbach's Alpha values were higher than the acceptable threshold (>0.7), table 2 demonstrates that the research instrument was internally consistent. Similarly, the KMO and CR for all variables were more than 0.7 and 0.5, respectively. Furthermore, the overall variance for all the components was greater than 0.6. Additionally, the p-values of Bartlett's tests were significant for all variables.

3.2 Structural Equation Modeling (SEM) and Results

Structural Equation Modeling (SEM) serves the specific purpose of confirming numerous theoretical models that elucidate the relationships between variables and their underlying constructs. SEM enables an exploration of the connections between independent and dependent variables, which may encompass both measured and latent variables (Ullman, 2006).

Table 1. Summary of demographic factors

Category	Variables	Compositions	
		Frequency	Percentage (%)
Gender	Male	67	19.31
	Female	280	80.69
Studding Year	1st year	93	26.8
	2nd year	83	23.9
	3rd year	96	27.7
	4th year	75	21.6
Province	Western	106	30.5%
	Central	17	4.9%
	Eastern	5	1.4%
	North Central	23	6.6%
	Northwestern	53	15.3%
	Northern	1	0.3%
	Sabaragamuwa	42	12.1%
	Southern	81	23.3%
	Uva	19	5.5%
Computing Experience	Less than 2 years	77	22.19
	3-5 years	139	40.06
	6-8 years	77	22.19
	More than 8 years	54	15.56
Cloud Computing Experience	No experience	120	34.58
	1-2 years	159	45.82
	3-5 years	58	16.72
	6-8 years	8	2.31
	More than 8 years	2	0.58

SEM encompasses various techniques, with the most prevalent approaches being Covariance-Based SEM (CB-SEM) and Partial Least Squares (PLS). In this study, the primary analytical method employed is CB-SEM. CB-SEM utilizes a maximum likelihood technique, aiming to minimize the disparity between observed and estimated covariance matrices, as opposed to maximizing explained variance (Hair et al., 2010)

Measurement Model:

The measurement model defines the indicators for each construct and allows for a construct validity evaluation (Hair et al., 2010). Figure 2 displays a visual representation of the Confirmatory Factor Analysis model (CFA).

There are 53 observed variables and 13 variables that can be latent. The AMOS 21 program assigns the number one (1) to chosen arrows for model identification.

Table 2. Reliability and Validity of the measurement scale

Index	Cronbach Alpha	KMO	Bartlett's (p-value)	Total variance	Composite Reliability
BI	0.880	0.832	0.0000	73.940	0.884
ATC	0.948	0.866	0.0000	86.566	0.948
SN	0.867	0.672	0.0000	79.056	0.878
BC	0.899	0.839	0.0000	76.865	0.901
PEoU	0.927	0.902	0.0000	77.467	0.927
PU	0.932	0.905	0.0000	78.713	0.934
ST	0.918	0.844	0.0000	80.292	0.919
PR	0.872	0.825	0.0000	72.413	0.872
SC	0.845	0.726	0.0000	76.300	0.845
PC	0.877	0.870	0.0000	70.040	0.894
VL	0.853	0.734	0.0000	66.911	0.853
SPR	0.906	0.849	0.0000	78.101	0.907
TR	0.873	0.833	0.0000	72.476	0.874

Table 3. Summaries of the goodness of fit indices for measurement model

Goodness of fit Index		Acceptable Value	Observed value
Absolute fit indices	CMIN/DF	< 3	1.666
	GFI	0 - 1	0.826
	AGFI	0 - 1	0.799
	RMSEA	< 0.1	0.044
	RMR	< 0.1	0.032
Incremental fit indices	TLI	0 - 1	0.941
	CFI	0 - 1	0.946
	RFI	0 - 1	0.863
	NFI	0 - 1	0.877
Parsimony fit indices	PGFI	0 - 1	0.717
	PRATIO	0 - 1	0.902
	PNFI	0 - 1	0.791
	PCFI	0 - 1	0.854

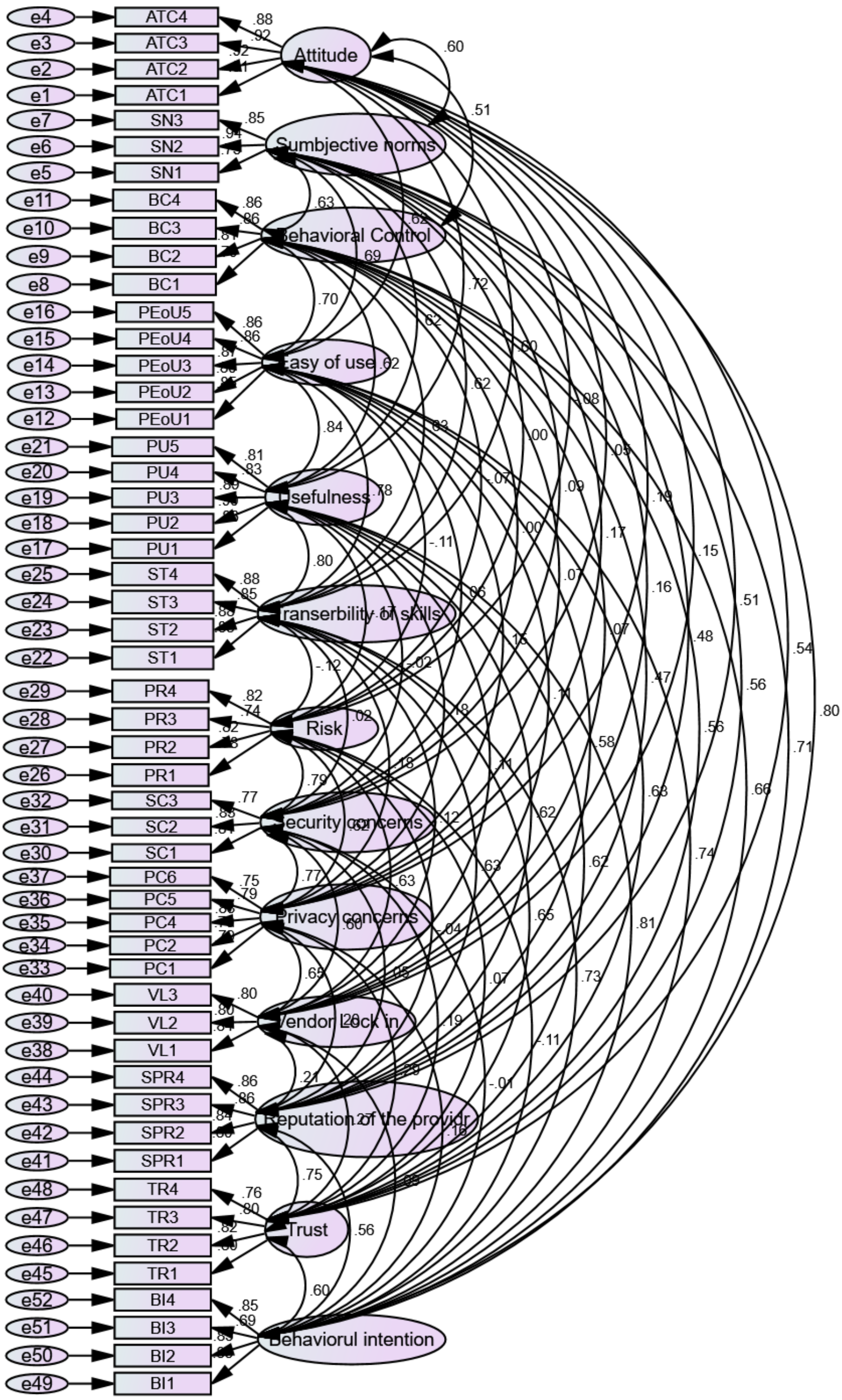

Figure 2. Measurement model with standardized estimates

Goodness of Fit of the Measurement Model:

Table 3 displays the measurement model's goodness of fit indices. According to table 3, the CMIN / DF value was 1.666, which was less than 3. The RMSEA was 0.044 and the RMR was 0.032. Both results were within the acceptable range of 0.1. Furthermore, the GFI value (0.826) was greater than the PGFI value (0.717). As a consequence, it is possible to conclude that there was no multicollinearity issue. Moreover, all other values were between 0 and 1. As a result, the model's validity was confirmed.

Table 4 presents the findings of the convergent validity of the measurement model. The suggested level of standardized factor loadings for reflective indicators was 0.5 or more than 0.70, per Hair et al. (2010). All the standardized factor loadings are greater than 0.7 and significant at 5%, as Table 4 demonstrates. Refer to appendix C. Additionally, every composite dependability metric is greater than 0.7 and every AVE number is greater than 0.6. Consequently, it may be concluded that convergent validity requirements are not problematic.

Table 5 shows that the non-diagonal entries are the squared inter-construct correlation estimates for constructs, whereas the diagonal items (bold in table 5) are the AVE for all constructs. Each construct's AVE was higher than the squared correlations between it and the other constructs, as seen in Table 5. Consequently, discriminant validity is unaffected.

The following three factors predicted perceived risks: perceived privacy concerns, perceived security concerns, and Vendor lock-in. Perceived privacy concerns have an insignificant positive relationship with overall perceived risks (β = 0.080, P = 0.364). However, as proven in the past in perceived privacy concerns have a considerable influence on perceived risks (Li & Chang, 2012a). However, perceived privacy concerns had not had a significant influence on the total level of perceived risk among university students in the Sri Lanka context. Concerns related vendor lock-in and perceived security concerns, on the other hand, have a significant positive association with the overall level of perceived risks (β = 0.328, P = 0.001 and β = 0.669, P = 0.001, respectively).

Table 4. Convergent validity testing results

Construct	Number of Items	Standardized Factor Loadings		Average Variance Exacted (AVE)	Composite Reliability
		Min	Max		
BI	4	0.689	0.855	0.657	0.884
ATC	4	0.877	0.924	0.822	0.948
SN	3	0.728	0.937	0.707	0.878
BC	4	0.795	0.864	0.694	0.901
PEoU	5	0.797	0.87	0.718	0.927
PU	5	0.807	0.903	0.738	0.934
ST	4	0.831	0.882	0.738	0.919
PR	4	0.743	0.824	0.631	0.872
SC	3	0.773	0.827	0.645	0.845
PC	5	0.746	0.834	0.627	0.894
VL	3	0.799	0.837	0.660	0.853
SPR	4	0.801	0.863	0.709	0.907
TR	4	0.762	0.824	0.635	0.874

Table 5. Square of inter-construct correlations and the AVE for all constructs

	TR	ATC	SN	BC	PEoU	PU	ST	PR	SC	PC	VL	SPR	BI
TR	**0.635**												
ATC	0.538	**0.822**											
SN	0.558	0.604	**0.707**										
BC	0.560	0.514	0.634	**0.694**									
PEoU	0.629	0.617	0.694	0.696	**0.718**								
PU	0.624	0.718	0.619	0.618	0.840	**0.738**							
ST	0.654	0.596	0.616	0.626	0.776	0.798	**0.738**						
PR	0.068	-0.078	0.000	-0.065	-0.105	-0.170	-0.116	**0.631**					
SC	0.190	0.053	0.094	-0.003	0.059	-0.017	0.019	0.791	**0.645**				
PC	0.290	0.186	0.166	0.074	0.147	0.178	0.177	0.616	0.770	**0.627**			
VL	0.265	0.152	0.163	0.066	0.108	0.109	0.115	0.632	0.596	0.650	**0.660**		
SPR	0.747	0.509	0.483	0.475	0.577	0.623	0.629	-0.038	0.050	0.202	0.213	**0.709**	
BI	0.599	0.800	0.711	0.662	0.742	0.810	0.728	-0.112	-0.011	0.164	0.089	0.557	**0.657**

Structural Model:

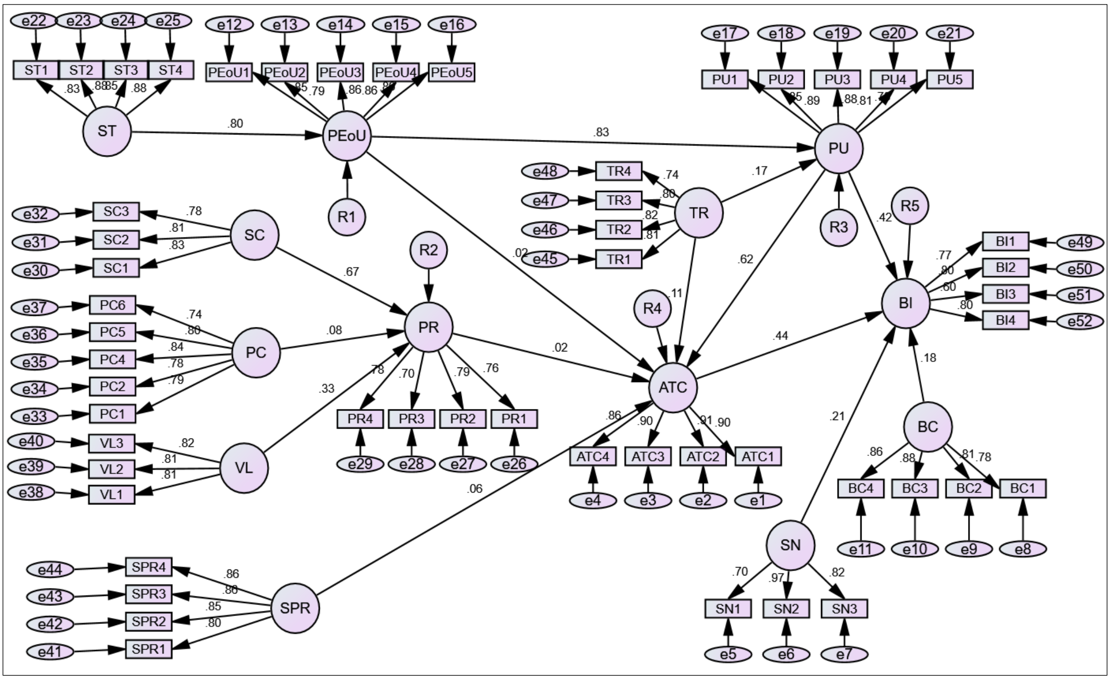

Figure 3. Structural model for direct relationship BI and endogenous constructs

This finding is also verified by the study conducted by Li & Chang (2012a). Trust in cloud computing providers has a significant positive relationship with overall perceived usefulness (β = 0.168, P = 0.001). However, according to prior research, trust in cloud computing providers does not significantly influence the total perceived usefulness (Alotaibi, 2014). However, trust in cloud computing providers had a significant influence on the total level of perceived usefulness among university students in the Sri Jayewardenepura context.

Furthermore, Perceived ease of use shows a strong positive association with the total level of Perceived usefulness (β = 0.825 P = 0.001). It demonstrates that increasing perceived ease of use can increase total perceived usefulness. This is also verified by previous studies (Alotaibi, 2014; Burda & Teuteberg, 2014; Li & Chang, 2012a).

Testing Model Hypotheses:

Table 6. Results of regression weights of structural model

Path	Status	Standardized path coefficients	Standard error	P-value	Decision
BC → BI	Direct	0.182	0.063	0.003	Supportive
SN → BI	Direct	0.212	0.078	0.002	Supportive
PU → BI	Direct	0.420	0.076	0.001	Supportive
ATC → BI	Direct	0.436	0.073	0.001	Supportive
TR → ATC → BI	Indirect	0.165	0.047	0.001	Supportive
SPR → ATC → BI	Indirect	0.028	0.029	0.343	Not Supportive
VL → PR → ATC → BI	Indirect	0.003	0.007	0.700	Not Supportive
PC → PR → ATC → BI	Indirect	0.001	0.003	0.743	Not Supportive
SC → PR → ATC → BI	Indirect	0.005	0.014	0.700	Not Supportive
ST → PEoU→ ATC → BI	Indirect	0.461	0.060	0.001	Supportive
PEoU → PU → BI	Indirect	0.578	0.059	0.001	Supportive
PR → ATC → BI	Indirect	0.008	0.021	0.700	Not Supportive
PU → ATC → BI	Indirect	0.272	0.067	0.001	Supportive
VL → PR	Direct	0.328	0.069	0.001	Supportive
PC → PR	Direct	0.080	0.090	0.364	Not Supportive
SC → PR	Direct	0.669	0.086	0.001	Supportive
TR → PU	Direct	0.168	0.050	0.001	Supportive
PEoU → PU	Direct	0.825	0.041	0.001	Supportive
ST → PEoU	Direct	0.797	0.041	0.001	Supportive
TR → ATC	Direct	0.113	0.073	0.110	Not Supportive
SPR → ATC	Direct	0.064	0.067	0.343	Not Supportive
PEoU → ATC	Direct	0.016	0.122	0.858	Not Supportive
PR → ATC	Direct	0.019	0.047	0.700	Not Supportive
PU → ATC	Direct	0.623	0.115	0.001	Supportive
ST → PEoU → PU	Indirect	0.657	0.057	0.001	Supportive
TR → PU → ATC	Indirect	0.104	0.035	0.001	Supportive
VL → PR → ATC	Indirect	0.006	0.016	0.700	Not Supportive
PC → PR → ATC	Indirect	0.001	0.006	0.743	Not Supportive
SC → PR → ATC	Indirect	0.012	0.031	0.700	Not Supportive
ST → PEoU → ATC	Indirect	0.422	0.064	0.001	Supportive
PEoU → PU → ATC	Indirect	0.514	0.098	0.001	Supportive

Furthermore, perceived transferability of computer skills (β = 0.657, P = 0.001) shows an indirect significant positive association with perceived usefulness. Moreover, there is a substantial positive relationship between perceived transferability of computer skills and overall degree of perceived ease of use (β = 0.797, P = 0.001). This confirmed the thesis that there is a large positive association between perceived transferability of computer skills and perceived ease of use (Li & Chang, 2012a).

Conversely, the following five factors predicted attitudes toward cloud computing: trust in cloud computing providers, the provider's perceived reputation, perceived ease of use, perceived usefulness, and perceived risks. Perceived usefulness was the only variable in this study that was shown to be statistically significant. Previous research has confirmed that perceived usefulness has a significant relationship with attitudes toward cloud computing (Alotaibi, 2014; Li & Chang, 2012a).

Moreover, Trust of cloud computing providers, the perceived reputation of the provider, perceived ease of use, and perceived risks were not statistically significant for the overall degree of attitude toward cloud computing, according to this study. Previous research has shown that perceived ease of use has a substantial influence on the overall degree of attitude toward cloud computing (Alotaibi, 2014; Li & Chang, 2012a). Li & Chang (2012a) also identified a substantial negative association between perceived risks and attitude toward cloud computing. Furthermore, Li & Chang (2012a) revealed a significant favorable association between the provider's perceived reputation and attitude toward cloud computing.

However, trust in cloud computing providers, perceived reputation of the provider, perceived ease of use, and perceived risks had no significant effect on the overall degree of attitude toward cloud computing among Sri Jayewardenepura university students. Trust in cloud computing providers (β = 0.104, P = 0.001) has an indirect substantial positive relationship with cloud computing attitude. Furthermore, perceived transferability of computer skills (β = 0.422, P = 0.001) and perceived ease of use (β = 0.514, P = 0.001) show an indirect significant positive relationship with Attitude toward cloud computing. However, concerns about vendor lock-in (β = 0.006, P = 0.7), perceived security concerns (β = 0.012, P = 0.7), and perceived privacy concerns (β = 0.001, P = 0.743) had an indirect insignificant positive relationship with attitudes toward cloud computing. The following four factors predicted intention to use cloud computing: Perceived Usefulness, Perceived Behavioral Control, Subjective norms, and Attitudes toward cloud computing. According to the study, all the factors were statistically significant. Behavioral control has a significant positive relationship with total behavioral intention to use cloud computing (β = 0.182, P = 0.003). Li & Chang (2012a) discovered that behavioral control was highly related to overall behavioral intention to use cloud computing. Similarly, subjective norms show a considerable positive relationship with overall behavioral intention to use cloud computing (β = 0.212, P = 0.002). This is also confirmed by previous studies which state in their studies that behavioral intention to use cloud computing was significantly influenced by subjective norms (Li & Chang, 2012a; Shin, 2013),. Perceived usefulness has a significant positive relationship with the overall level of Behavioral intention to use cloud computing (β = 0.420, P = 0.001).

Also, perceived usefulness shows an indirect significant positive association with overall behavioral intention to use cloud computing (β = 0.272, P = 0.001). This finding is consistent with Li & Chang, 2012a), who reported that behavioral intention to use cloud computing is significantly influenced by perceived usefulness. Furthermore, attitude toward cloud computing was found to have a positive and significant effect on behavioral intention to use cloud computing (β = 0.436, P = 0.001). Previous studies have also confirmed this relationship, highlighting the significant association between attitude toward cloud computing and behavioral intention to adopt it (Alotaibi, 2014; Li & Chang, 2012a).

4. Conclusion and Recommendations

4.1 Conclusions

This study aimed to identify and analyze the factors influencing undergraduate students' behavioral intentions towards adopting cloud computing, focusing on perceived risks, attitudes, and behavioral intentions. The research uncovered several critical insights that can guide educational institutions and cloud service providers in promoting cloud computing adoption. Firstly, the study established that perceived concerns, including security and vendor lock-in, significantly impact perceived risks associated with cloud computing. These findings highlight the necessity for cloud service providers to address these concerns by enhancing security measures and providing transparent policies to mitigate fears related to vendor lock-in. Secondly, perceived usefulness emerged as a pivotal factor in shaping students' attitudes towards cloud computing. Educational institutions can leverage these findings by emphasizing the practical benefits and ease of use of cloud technologies in their curricula. Finally, the study found that attitudes towards cloud computing, perceived usefulness, subjective norms, and perceived behavioral control significantly influence students' behavioral intentions to adopt cloud computing. Institutions should consider implementing training programs and support systems to enhance students' confidence and ease of use of these technologies, thus fostering a more positive attitude towards their adoption.

4.2 Recommendations

As the research underscores, perceived usefulness is a key driver of students' behavioral intentions to use cloud services. Educational institutions should emphasize the practical utility of cloud computing in enhancing students' learning experiences. This can be achieved through the integration of cloud-based tools and resources that directly contribute to students' academic success. Additionally, the perceived ease of use indirectly influences students' behavioral intentions. Therefore, academic policies should prioritize the user-friendliness of cloud services. Training and support programs can be established to familiarize students with cloud platforms and reduce any perceived barriers to entry. Furthermore, the perceived transferability of computer skills is a factor that indirectly affects students' behavioral intentions. Educational institutions can provide opportunities for students to develop and enhance their digital literacy and computer skills. Offering courses or workshops on using cloud applications can be beneficial. Trust in cloud computing providers and their services is crucial. Academic policies should promote transparency and data security to build trust among students. Clearly communicating data privacy and security measures is essential. Collaborating with reputable cloud service providers can also enhance trust. Lastly, attitudes toward cloud computing play a partially mediating role in students' intentions. Academic institutions should aim to foster positive attitudes by highlighting the benefits of cloud services. Encouraging faculty to integrate cloud-based technologies into their teaching can also influence students' perceptions positively.

5. References

Achjari, D. (2004). *Partial Least Squares: Another Method of Structural Equation Modeling Analysis*. *19*, 11.

Ajzen, I. (1991). *The Theory of Planned Behavior*. *50*.

Almajalid, R. M. (2017). *A Survey on the Adoption of Cloud Computing in Education Sector*. 12.

Alotaibi, M. B. (2014). Exploring Users' Attitudes and Intentions Toward the Adoption of Cloud Computing in Saudi Arabia: An Empirical Investigation. *Journal of Computer Science*, *10*(11), 2315–2329. https://doi.org/10.3844/jcssp.2014.2315.2329

Ambrose, P., & Chiravuri, A. (2010). *An Empirical Investigation of Cloud Computing for Personal Use*. 6.

Avram, M. G. (2014). Advantages and Challenges of Adopting Cloud Computing from an Enterprise Perspective. *Procedia Technology*, *12*, 529–534. https://doi.org/10.1016/j.protcy.2013.12.525

Awa, H. O., Ukoha, O., & Emecheta, B. C. (2016). Using T-O-E Theoretical Framework to Study the Adoption of ERP Solution. *Cogent Business & Management*, *3*(1), 1196571. https://doi.org/10.1080/23311975.2016.1196571

Bagozzi, R. R., & Yi, Y. (1988). *On the Evaluation of Structural Equation Models*. 21.

Bairagi, S. I., & Bang, A. O. (2015). *Cloud Computing: History, Architecture, Security Issues*. 8.

Bamiah, M. A., & Brohi, S. N. (2013). Seven Deadly Threats and Vulnerabilities in Cloud Computing. *Vol No.*, *9*, 5.

Behrend, T. S., Wiebe, E. N., London, J. E., & Johnson, E. C. (2011). Cloud Computing Adoption and Usage in Community Colleges. *Behaviour & Information Technology*, *30*(2), 231–240. https://doi.org/10.1080/0144929X.2010.489118

Bogataj Habjan, K., & Pucihar, A. (2017). The Importance of Business Model Factors for Cloud Computing Adoption: Role of Previous Experiences. *Organizacija*, *50*(3), 255–272. https://doi.org/10.1515/orga-2017-0013

Burda, D. (2014). Understanding the Benefit Structure of Cloud Storage as a Means of Personal Archiving—A Choice—Based Conjoint Analysis. *Tel Aviv*, 23.

Burda, D., & Teuteberg, F. (2014). The Role of Trust and Risk Perceptions in Cloud Archiving—Results from an Empirical Study. *The Journal of High Technology Management Research*, *25*(2), 172–187. https://doi.org/10.1016/j.hitech.2014.07.008

Buyya, R., Yeo, C. S., Venugopal, S., Broberg, J., & Brandic, I. (2009). Cloud Computing and Emerging IT Platforms: Vision, Hype, and Reality for Delivering Computing as the 5th Utility. *Future Generation Computer Systems*, *25*(6), 599–616. https://doi.org/10.1016/j.future.2008.12.001

Davis, F. (1985). *A Technology Acceptance Model for Empirically Testing New End-User.*

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

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. https://doi.org/10.1287/mnsc.35.8.982

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding Determinants of Cloud Computing Adoption Using an

Integrated TAM-TOE Model. *Journal of Enterprise Information Management*, *28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065

Ghanem, D. B. M. (2019). *Application Of Cloud Computing In The Field Of Education: Google Apps As An Example*. *3*(6), 10.

Hair, J., William, B., Barry, B., & Rolph, A. (2010). *Overview of Multivariate Methods* (7th edition).

Hu, L., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, J., & Nicol, D. M. (2013). Trust Mechanisms for Cloud Computing. *Journal of Cloud Computing: Advances, Systems and Applications*, *2*(1), 9. https://doi.org/10.1186/2192-113X-2-9

Hussein, N. H., & Khalid, A. (2016). *A Survey of Cloud Computing Security Challenges and Solutions*. *14*(1), 5.

Lei, P.-W., & Wu, Q. (2007). Introduction to Structural Equation Modeling: Issues and Practical Considerations. *Educational Measurement: Issues and Practice*, *26*(3), 33–43. https://doi.org/10.1111/j.1745-3992.2007.00099.x

Li, Y., & Chang, K. (2012). *A Study on User Acceptance of Cloud Computing: A Multi-Theoretical Perspective*. 11.

Lian, J.-W., Yen, D. C., & Wang, Y.-T. (2014). An Exploratory Study to Understand the Critical Factors Affecting the Decision to Adopt Cloud Computing in Taiwan Hospital. *International Journal of Information Management*, *34*(1), 28–36. https://doi.org/10.1016/j.ijinfomgt.2013.09.004

Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., & Ghalsasi, A. (2009). *Cloud Computing – The Business Perspective*. 34.

McDonald, R. P., & Ho, M.-H. R. (2002). Principles and Practice in Reporting Structural Equation Analyses. *Psychological Methods*, *7*(1), 64–82. https://doi.org/10.1037/1082-989X.7.1.64

Mell, P., & Grance, T. (2011). *The NIST Definition of Cloud Computing*. 7.

Miller, M. (2009). *Cloud computing: Web-based applications that change the way you work and collaborate online*. Que. http://www.myilibrary.com?id=261002

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin*, *105*(3), 430–445. https://doi.org/10.1037/0033-2909.105.3.430

Noor, T. H., Sheng, Q. Z., Zeadally, S., & Yu, J. (2013). Trust management of services in cloud environments: Obstacles and solutions. *ACM Computing Surveys*, *46*(1), 1–30. https://doi.org/10.1145/2522968.2522980

Ratten, V. (2012). Cloud Computing Services: Theoretical Foundations of Ethical and Entrepreneurial Adoption Behaviour. *International Journal of Cloud Applications and Computing*, *2*(2), 48–58. https://doi.org/10.4018/ijcac.2012040105

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed). Free Press; Collier Macmillan.

Sarkar, A. (2008). *E-Commerce Adoption and Implementation in SMEs: An Analysis of Factors*. 11.

Shana, Z., & Abulibdeh, E. (2017). Cloud Computing Issues for Higher Education:

Theory of Acceptance Model. *International Journal of Emerging Technologies in Learning (IJET)*, *12*(11), 168. https://doi.org/10.3991/ijet.v12i11.7473

Shin, D.-H. (2013). User centric cloud service model in public sectors: Policy implications of cloud services. *Government Information Quarterly*, *30*(2), 194–203. https://doi.org/10.1016/j.giq.2012.06.012

Sondhi, N. (2011). Jonathan Wilson, *Essentials of Business Research—A Guide to Doing Your Research Project*. New Delhi: SAGE Publications India Pvt Ltd, 2010, 316 pp. Rs 495 (ISBN: 978-81-321-0567-1[Pb]). *Global Business Review*, *12*(2), 343–344. https://doi.org/10.1177/097215091101200211

Sultan, N. (2010). Cloud computing for education: A new dawn? *International Journal of Information Management*, *30*(2), 109–116. https://doi.org/10.1016/j.ijinfomgt.2009.09.004

Ullman, J. B. (2006). Structural Equation Modeling: Reviewing the Basics and Moving Forward. *Journal of Personality Assessment*, *87*(1), 35–50. https://doi.org/10.1207/s15327752jpa8701_03

Voas, J., & Zhang, J. (2009). Cloud Computing: New Wine or Just a New Bottle? *IT Professional*, *11*(2), 15–17. https://doi.org/10.1109/MITP.2009.23

Wang, C., Chow, S. S. M., Wang, Q., Ren, K., & Lou, W. (2013). Privacy-Preserving Public Auditing for Secure Cloud Storage. *IEEE Transactions on Computers*, *62*(2), 362–375. https://doi.org/10.1109/TC.2011.245

Wang, C., Ren, K., & Lou, W. (2013). *Privacy-Preserving Public Auditing for Secure Cloud Storage*. 12.

Wang, J., & Verma, A. (2012). Explaining organizational responsiveness to work-life balance issues: The role of business strategy and high-performance work systems. *Human Resource Management*, *51*(3), 407–432. https://doi.org/10.1002/hrm.21474

Wyld, D. C. (2010). The Cloudy Future of Government it: Cloud Computing and the Public Sector Around the World. *Semantic Technology*, *1*(1), 21.

Zamani, A. T. (2014). The Impact of the Cloud Based M-Learning in Higher Education. *International Journal of Advanced Research in Computer Science and Software Engineering*, *4*(1).