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ABSTRACT

The explosive growth of data and frequent application updates along with the increasing need to access data and/or applications from multiple locations has resulted in a need to improve the way data and applications are stored and served. Such a need has forced both companies and academic institutions to pay attention to cloud computing technology. Since education is a driving force for the continuous improvement of cloud computing, this study aims at identifying the factors that influence college students' intention to learn about cloud computing technology. Specifically, the research question focuses on determining which factors drive students' intention to learn the cloud computing concept. Four hundred and thirty-five (435) college students participated in this study. The results revealed several factors which influence students' intention to learn cloud computing and thus were recommended as the factors academic institutes should consider before adding cloud computing into their curriculum.

Keywords: Cloud Computing, Technology Acceptance Model, Perceived Usefulness, Perceived Ease Of Use, Perceived Security, Perceived Speed, Perceived Cost, Normative Beliefs, Technology Competency, COVID-19 Impact

INTRODUCTION

Cloud computing has seen an increasing rise in demand and diffusion (Burda and Teuteberg 2016). The cloud is a unique platform for generating data and innovative solutions to leverage that data (Ikink 2021). Cloud computing has profound impacts on today's business environment (Fan, Wu, Chen, and Fang, 2015) by providing on-demand services including storage, communications, and computation (Chen, Liu, Gallagher, Pailthorpe, Sadiq, Shen, and Li, 2012). Several business models have changed to incorporate a wide variety of cloud computing environments (Barett 2020). This technology has attracted considerable attention because cloud services offer numerous benefits including the ability to provide faster on-demand infrastructure, self- service, and the independent ability to contribute to and access resources (Lee 2019). It is increasingly growing in convenience as a ubiquitous network that requires little interaction between the cloud service provider and the user (Changchit and Chuchuen 2018). This flexibility and independence can help save users time and stress by making the process simple and allowing the account design to be based entirely on individual needs.

Cloud computing innovations aim at enhancing users' experience through smart and interactive technologies that are customizable, scalable, and reliable (Khansa and Zobel 2014). The cloud computing model has become tremendously popular due to its benefits such as cost- effectiveness, scalability, usefulness, ease of use, and worldwide accessibility. Since 2010, the global cloud services industry has risen year-over-year to reach a $370 billion valuation in 2020, indicating a growth of over 380 percent in ten short years (Ikink 2021). Cloud computing adoption is exploding, with enterprise applications migrating to the public cloud and organizations becoming more cloud-native in their deployments (Costello 2021).

Cloud computing has attracted a significant amount of attention in both commercial and academic settings. Education is a driving force for the continuous improvement of cloud computing (Changchit et al. 2018). As such, businesses are now requiring some degree of cloud computing skills from their new hires. Thus, it is in the best interest of current students to learn about how to operate in a cloud environment.

In addition to providing students with in-demand skills, cloud computing can also provide a number of benefits to an educational setting (Behrend, Wiebe, London, and Johnson 2011). Students can gain a lot from this technology as it serves as a convenient mobile storage space (Singh and Veralakshmi 2012).

Some of the benefits that students can derive from cloud computing, in an educational setting, include using it for completing assignments, online classes, group projects, creating and editing papers and presentations; as well as for work

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or entertainment (Changchit 2015). Thus, students are both learning about cloud computing and at the same time using this technology to assist with their education. For students, the attractiveness of cloud computing is not only the immediate benefits that cloud computing provides them, but it also the desire that students today have for new technology, both of which make learning and adopting cloud computing easier for them. Many companies believe that today's graduates are lacking work-appropriate skills (Cronin, Allen, Ellison, Marchant, Levy, and Harwood 2019). Integrating cloud computing concepts and applications into the curriculum provides students with skills and competency development directly related to today's workplace (Mitchell and Meggisson 2014). With many benefits generated by cloud computing technology, it is interesting to find out how students perceive cloud computing and which factors can drive their intentions to learn this technology.

The remainder of this paper is as follows: section 2 provides an overview of the literature on the cloud computing adoption; section 3 describes the theoretical framework and the proposed model for this study; section 4 lays out the research methodology; section 5 presents the data analysis and results; section 6 discusses the implications of this study; and section 7 concludes the paper and outlines future opportunities.

LITERATURE REVIEW

Technology will continue to grow and evolve at a rapid pace (Marquardson 2020). The explosive growth of data driven by information and communication has caused a need for improving the way that data are stored and retrieved.

Over the past decade, the phrase "data is currency" has permeated corporate culture from Silicon Valley to Stockholm to Sydney (Ikink 2021). Technological advances, such as mobile devices, social media, and cloud computing, help companies gain competitive and strategic advantages (Lee 2019). The high demand for more advanced and efficient technology has contributed to the creation of new advancements in technology such as cloud computing.

Cloud Computing has transformed the Information Technology (IT) industry by opening the possibility for cloud computing services to deliver the enterprise applications and software through platforms such as Amazon Elastic Cloud, Microsoft's Azure, Google App Engine as a service (SaaS).

Cloud computing has been defined in various ways in previous studies (e.g., Buyya, Yeo, Venugopal, Broberg, and Brandic 2009; Vouk 2008).

The National Institute of Standards and Technology (NIST) defined cloud computing as a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks,

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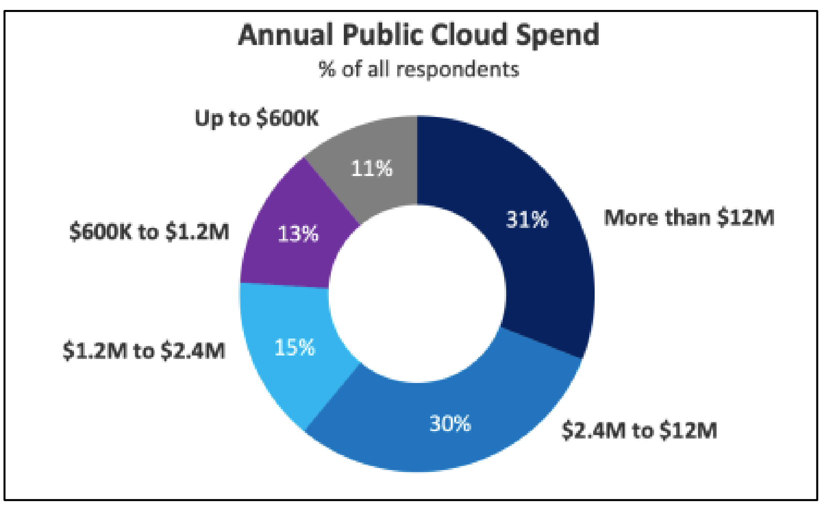
servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (Mell and Grance 2011). The popularization of cloud computing by companies like Amazon®, Google®, and Apple® ensure that the usage of the cloud as a storage medium for music, movies, and other media content files, becomes ubiquitous and in high demand. Many research institutes and consulting firms expect this technology to contribute to the national economy through increasingly efficient operations, cost reduction, and new market development (Park and Kim 2019).

The global revenue of cloud computing usage and trend are continually increasing every year since 2005 (Rightscale, 2014). Even before COVID-19, cloud computing adoption was expanding rapidly (Flexera 2021). The urgent changes due to COVID-19's impact caused these plans and adoption to increase at an even greater rate. Flexera (2021) conducted a study in October and November 2020. Their study explores what 750 global cloud decision makers and users think about the public, private and multi-cloud market. As revealed in this report, the increasing use of public cloud is driving up cloud spending for organizations of all sizes. Public cloud spending is now a significant line item in IT budgets, especially among larger organizations.

As shown in Figure 1, 31 percent of the respondents (compared to 16 percent last year) reported annual spending of at least $12 million on public cloud services, while 76 percent spend $1.2 million or more per year (Flexera, 2021).

Figure 1. Public cloud spends for all organizations (Source: Flexera, 2021)



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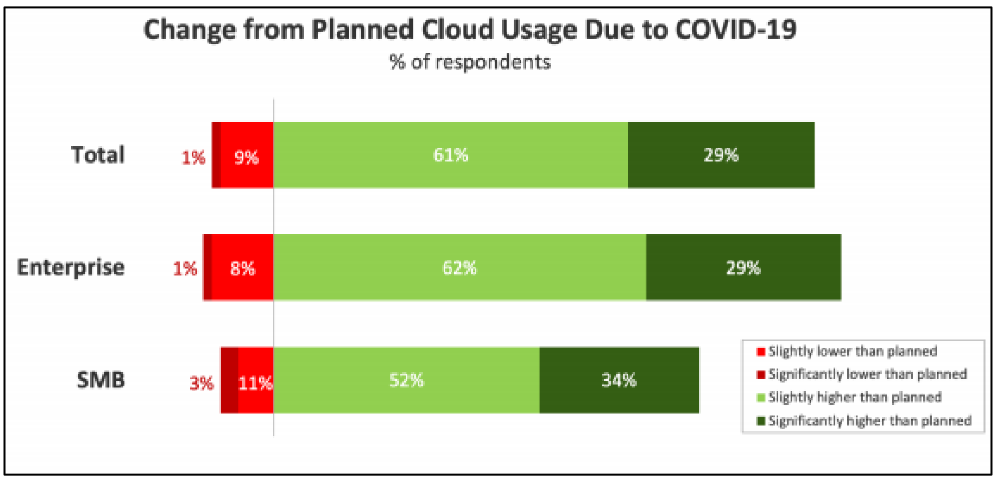
COVID – 19 IMPACT ON CLOUD COMPUTING PLAN

As a response to the impact of COVID-19, the study conducted by Flexera (2021) also sought to investigate how the pandemic might impact cloud strategy planned before COVID-19. The result revealed that the cloud plans and adoption have clearly shifted as a result of the pandemic. The participants indicated how organizations expect COVID-19 to affect their cloud plans. As shown in Figure 2, 90 percent of the responses reported cloud usage to be higher than initially planned. Such an increase is the result of the extra capacity needed for current cloud-based applications to meet increased demand as online usage grows (Flexera, 2021).

Figure 2. COVID-19 impact on planned cloud usage for all organizations (Source: Flexera, 2021)



Cloud Computing in Academics

In academic settings, cloud computing is a promising prospect for educational institutions, especially during times of budget constraints. Previous research on cloud computing in educational environments include works evaluating the impact of cloud computing in education (e.g., Hu and Zhang 2010; Tian, Su, and Lu 2010; Vaquero 2011). Additional research on cloud computing adoption in educational settings has focused its efforts on understanding the drivers and constraints that students and schools perceive in the adoption of this computing model. For example, Behrend et al (2011) examined the factors leading to adopting cloud

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computing as a virtual computing lab for a class. Their findings revealed that students' ease of use perception would positively affect intentions for future use, but not for actual use. In addition, students who complete their work faster and in a more practical manner were more likely to recognize cloud computing as an effective service.

Cloud services have been widely recognized as one of the potentials means to facilitate students' learning (Huang, 2017). A study introduced cloud computing to the construction of the digital learning environment for its on-demand services with high reliability, scalability and availability in the distributed environment (Ding and Xiong, 2015).

The results revealed that the co-construction and sharing model and incentive mechanism of a digital learning environment based on cloud computing (DLECC) may provide meaningful learning support and interactive communities and promote the co-construction of befitting educational resources. Behrend et al.'s (2011) study also found that students with anxiety about new technologies had a negative effect on the perceived usefulness of new technologies. Another study also suggested that in order to deal with technology anxiety, it is important for universities to plan hands-on training to help students become more familiar with these new technologies (Blue and Tirotta 2011).

Cloud computing is becoming increasingly popular as a way to deliver technology to secondary and postsecondary education environments and other organizations (Behrend et al. 2011). With several benefits promised by cloud computing, it is not surprising that the demand for graduates with exposure to cloud computing is on the rise (Changchit 2015; Chen et al. 2012). Integrating cloud computing concepts and applications into the business curriculum provides skill and competency development related directly to today's workplace (Mitchell and Meggison 2014).

Despite the advantage of cloud storage compared to conventional storage media, very few studies have focused on students' willingness to learn cloud technology. Changchit (2015) revealed several factors that play a significant role in encouraging students to accept cloud computing. These factors included perceived usefulness, perceived ease of use, perceived security, perceive speed of access, and perceived cost of usage. Another study investigated the beliefs and perceptions of school principals in Sweden toward cloud computing (Lim, Grönlundb, and Andersson, 2015). Results suggested principals of Swedish schools believe the main benefits of cloud computing is its ability to allow users to access data and software anywhere and its ability to facilitate sharing of learning materials and data.

Universities and students have limited resources that restrict the number of courses offered or that a student may take (Larson, Sanders, and Bohler 2021). Curriculum reforms that enable students' development of broader skills linked to employment are critical (Bone and Ross 2019). Therefore, in order to increase the potential for success, it is crucial for any institution to understand which factors can motivate

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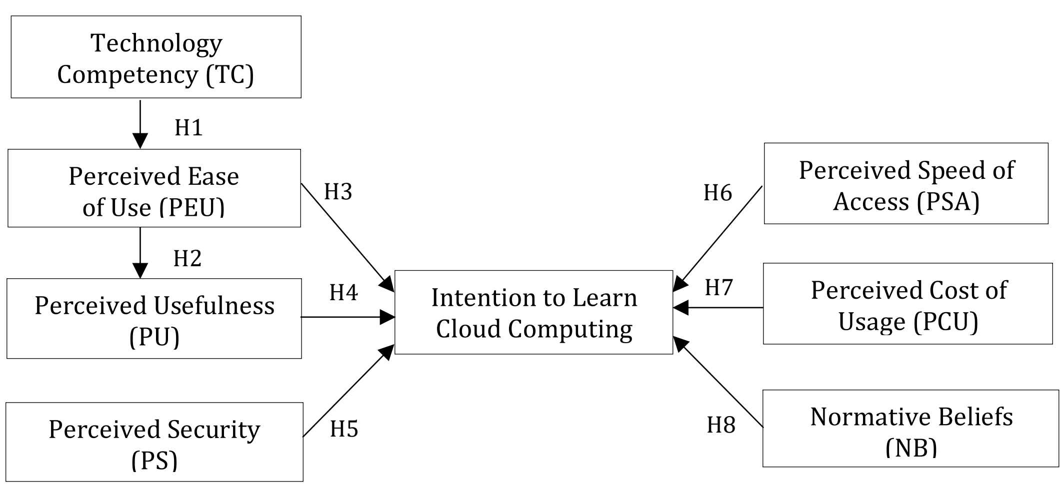
students to learn about cloud computing before integrating it into the curriculum. The findings in this study should help programs to focus on the factors that encourage students to develop an interest in the topic as well as finding ways to minimize the effect of discouraging factors, thus increasing the chance for the success of the integration of cloud computing into the program. Therefore, this study aims at examining the factors which impact students' willingness to learn cloud computing.

THEORETICAL DEVELOPMENT AND RESEARCH MODEL

The theoretical framework for this study is based the Technology Acceptance Model (TAM). TAM was developed by Davis in 1986 as an adaptation of the Theory of Reason Action (TRA) meant to be applied specifically to the field of information systems. The TAM introduces the factors impacting users' acceptance of information technology (Davis, Bagozzi, and Warshaw 1989). The TAM is widely used in many disciplines including educational settings and has been extended to include more relevant factors relating to various research topics. This study modified the TAM to include five additional factors predicted to play an important role in motivating students to learn cloud computing. These factors are: (1) Technology Competency (TC), (2) Perceived Security (PS), (3) Perceived Speed of Access (PSA), (4) Perceived Cost of Usage (PCU) and (5) Normative Beliefs (NB). The proposed research model is shown in Figure 3.

Figure 3. Research model



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Technology Competency (TC)

Technology competency is defined as an individual's assessment of their capability to use computers in a variety of situations (Hsia, Chang, and Tseng 2014). Typically, people are more likely to use an information system if they have a higher level of technology competency (Yang 2010). Ma and Liu (2005)

reported a positive effect between technology competency and intention to use internet-based applications. People with a higher level of technology competency tend to be more motivated to use technology to accomplish tasks as they have a higher level of confidence in their ability to accomplish the tasks using technology such as a computer. Regarding learning about the cloud computing topic, it is likely that students who are more technology competent will perceive the technology as easy to use. We therefore propose that:

H1: Technology Competency positively affects subjects' perceived of ease of use.

Perceived Ease of Use of Cloud Computing (PEU)

Prior studies focusing on behavior intention regarding technology have employed perceived ease of use as a contributing factor to behavioral intention (e.g., Park 2009; Venkatesh and Davis 1996). Perceived ease of use plays a crucial role in understanding individual responses to information technology (Chau and Hu 2001). This factor is defined as the degree to which the prospective user expects the target system to be free of effort (Davis et al. 1989). Based on the TAM, this factor has been shown to have an impact on perceived usefulness (Davis 1986). Several research studies over the past decade provide evidence that this factor also has a significant effect on behavioral intention (Venkatesh and Davis 2000). A study by Krahanna, Straub, and Chervany (1999) reported that behavioral intention toward an information system is influenced by perceived ease of use which also influences the perceived usefulness of an information system.

We thus hypothesize that:

H2: Perceived ease of use (PEU) positively affects subjects' perceived usefulness.

H3: Perceived ease of use (PEU) positively affects subjects' intention to learn cloud computing.

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Perceived Usefulness of Cloud Computing (PU)

Several prior studies exist that have reported an empirical link between perceived usefulness and behavioral intention (e.g., Jackson, Chow, and Leitch 1997; Venkatesh 1999). Davis et al (1989) define perceived usefulness as the prospective users' subjective probability that using a specific application system will increase their job performance within an organizational context. This factor has a significant impact on behavioral intention (Davis et al. 1989; Venkatesh and Davis 2000).

A prior study also reported that this construct positively influenced subjects' intention to adopt cloud computing (Changchit et al. 2018). Based on the foregoing, we propose the following hypothesis:

H4: Perceived usefulness (PU) positively affects subjects' intention to learn cloud computing.

Perceived Security of Cloud Computing (PS)

Security involves the protection from malevolent actors who are trying to exploit information for a variety of motives including self-indulgence, revenue generation, and even espionage (Bansal 2017). Bose, Luo, and Liu (2013) reported that perceived security is a crucial factor in the decision to employ cloud computing. Flavián and Guinalíu (2006) define perceived security as a subjective probability with which consumers believe that their personal data and information will not be viewed, stored, and manipulated during transit and storage by inappropriate parties in a manner that is inconsistent with their expectations. Security is usually a major concern for all individuals who are dealing with sensitive data in everyday life, there is a high likelihood that subjects would be more willing to learn about cloud computing if they find this technology to be secure. We therefore posit that:

H5: Perceived security (PS) positively affects subjects' intention to learn cloud computing.

Perceived Speed of Access of Cloud Computing (PSA)

The speed of using applications over the Internet can be a factor that has prevented cloud computing from being a viable option for both individuals and organizations. For cloud computing to be widely accepted, it is crucial that the services must allow users to access data at a reasonable speed (Changchit et al. 2018). Users may be unaware that the use of applications via the Internet still allow them to retrieve their

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data at the same speed as when the data is stored locally. Students' perception on the speed of access should influence their intention to learn about cloud computing. Hence, we posit that:

H6: Perceived speed of access (PSA) positively affects subjects' intention to learn cloud computing.

Perceived Cost of Usage of Cloud Computing (PCU)

In 2011, the monthly cloud expenditure of an average company was roughly $6,500. This number has risen to $10,000 per month in 2020 (Ikink 2021). A survey conducted by ComputerWorld magazine (Schultz 2011) of IT professionals revealed that while "saves money" ranked first on the list of cloud computing key benefits, "costs more" ranked third on the list of drawbacks suggesting that the issue of cost in outsourcing information technology resources is a complex issue. In many public and private sector industries, including education, federal and state government, and telecommunications, cloud computing systems are being pilot-tested and implemented to save IT costs and improve performance (Behrend et al. 2011). In addition, the cost of using the cloud is often a pay-as-you-go endeavor different from the typical flat price of equipment or software rental or purchase (Nanath and Pillai 2013). This adds a level of uncertainty to the perceived cost of usage of cloud computing. Thus, it is important to understand if this factor would have any impact on the decision to adopt cloud computing. If cloud computing is perceived as inexpensive, then students should be more willing to learn about cloud computing. Thus, students' perception of the cost of cloud computing should impact their willingness to learn this technology. We therefore hypothesize that:

H7: Perceived cost of usage (PCU) positively affects subjects' intention to learn cloud computing.

Normative Beliefs (NB)

According to Fishbein and Ajzen (1975) and their work on the TRA, normative beliefs can influence an individual's intention to perform a behavior. Fishbein and Ajzen (1975) defined normative beliefs as individuals' perception that most people who are important to them think they should or should not perform the behavior in question. Normative beliefs becomes an important factor shaping the direction in which consumers choose to do business (Changchit, Lonkani, and Sampet 2017). Regarding technology usage in an academic setting, Salleh (2016) found that normative beliefs have a positive influence on intention. Thus, we hypothesize:

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H8: Normative beliefs (NB) positively affects subjects' intention to learn cloud computing.

METHODOLOGY

Development of Measurement Instrument

The measurement scales for this study utilized the TAM survey instrument and modified it with the addition of five constructs. The perceive ease of use and perceived usefulness factor survey items were revised from the work of Venkatesh and Davis (2000) and Venkatesh, Morris, Davis, and Davis (2003). Other survey items to measure the additional factors in this study were developed to identify the significant constructs leading to students' intention to learn about cloud computing. Several tests such as reliability, KMO and Bartlett's, common method bias, and factor analysis were conducted in this study to verify and validate their suitability for the measurement model in this study. These results are described in the data analysis section of this paper.
The questionnaire consists of forty-seven (47) questions. Forty questions with the five-point Likert scale were designed to measure subjects' perceptions on cloud computing and whether they believe it should be integrated into their curriculum. The remaining seven questions were asked to gather some demographic data on the subjects. To validate the clarity of these questions, three professors and three researchers were asked to read through the survey questions. Revisions to the survey were made based on the feedback received.

Data Collection

The surveys were administered to students at a Southern university in the United States These students are certainly part of the target group for companies providing cloud computing services. Before collecting the data, the researcher contacted instructors to gain their consent to hand out the surveys in their classes. In each class, the researcher spent about ten minutes explaining the importance of the study and asked students to read each item carefully as their responses are very important to this study. Then, all students were provided with sufficient class time to respond to the survey. Students were informed that participation in the study was voluntary and that their responses would be kept anonymous. Four hundred and sixty-seven (467) subjects participated in this study. However, only four hundred and thirty-

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five (435) responses are valid. Details on the subjects' demographics are provided in Table 1.

Table 1. Subjects' demographics (n=435)

	No.	%		No.	%
Gender			**Ethnicity**		
Male	170	39.1	African	5	1.2
Female	223	51.3	Anglo	54	12.4
No answer	42	9.6	Asian	17	3.9
			Hispanic	92	21.2
Age			Native American	3	0.7
18 - 24	347	79.7	Other	0	0.0
25 - 34	48	11.0	No Answer	264	60.6
35 - 44	9	2.1			
45 and over	6	1.4	**Classification**		
No answer	25	5.8	Freshman	77	17.7
			Sophomore	136	31.3
First Generation College Student			Junior	115	26.4
Yes	158	36.3	Senior	41	9.4
No	217	49.9	Graduate	23	5.3
No answer	60	13.8	Other	0	0.0
			No answer	43	9.9

	No.	%		No.	%
College					
Business	217	49.9	**Employment Status**		
Education	34	7.8	Full-time	45	10.3
Liberal Art	56	12.9	Part-Time	196	45.1
Nursing	38	8.7	Un-employed	151	34.7
Science & Technology	43	9.9	No Answer	43	9.9
No answer	47	10.8			

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DATA ANALYSIS AND DISCUSSION

Table 2 summarizes the items measuring the attitude towards the intention to learn cloud computing and seven factors proposed to influence subjects' intention. All items use a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 2. Measure subscales, internal consistency, means (M), and standard deviation (SD)

	α	**M**	**SD**
Perceived Usefulness of Cloud Computing	0.877	3.68	0.79
Using cloud computing will better prepare me for professional work			
Using cloud computing will make me more competitive in the job market			
Using cloud computing will make me more efficient performing computer tasks			
Using cloud computing will make others more aware of my work			
Using cloud computing allows me to access my files 24x7 worldwide			
Perceived Ease of Use of Cloud Computing	0.892	3.40	0.82
It is easy to use applications via cloud computing			
It is easy to learn how to use applications via cloud computing			
It is easy to understand how cloud computing works			
It is easy to get help troubleshooting issues with the cloud computing			
It is easy to find vendors that offer cloud computing services			

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Table 2. Measure subscales, internal consistency, means (M), and standard deviation (SD)-continue

Perceived Security of Cloud Computing	0.889	3.32	0.74
The company that provides the service will protect my data from the theft			
The company that provides the service prevent unauthorized access to my files			
The company that provides the service have the means to prevent the loss of my data			
The company that provides the service be a technology leader			
The company that provides the service encrypt my data			
Perceived Speed of Access of Cloud Computing	0.931	3.65	0.81
The speed of using cloud computing is pretty fast			
The speed of using cloud computing is sufficient for backup and storage			
The speed of using cloud computing to upload/download files is pretty fast			
The speed of using cloud computing to work on files is pretty fast			
The speed of using cloud computing is good enough for my everyday			
Perceived Cost of Usage of Cloud Computing	0.904	3.49	0.81
The cost of using cloud computing is inexpensive for the amount of storage provided			
The cost of using cloud computing is less expensive than buying storage for a laptop/PC			
The cost of using cloud computing is inexpensive compared to cost of using other types of storages			
The cost of using cloud computing is worth for the value of using it			
The cost of using cloud computing is inexpensive as there is no maintenance cost			
Normative Beliefs	0.826	3.10	0.80
People around me think that I should use cloud computing			
My family thinks that I should use cloud computing			
My friends influence my decision to use cloud computing			
Cloud computing is the technology that everyone should be familiar with			
Using cloud computing makes me feel current in the trend			
Technology Competency	0.936	3.96	0.95
I like to learn new technology			
I am not afraid of using technology			
My ability to learn new technology is high			
I am always interested in new technology			
I enjoy working with technology			

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Table 2. Measure subscales, internal consistency, means (M), and standard deviation (SD)-continue

	α	M	SD
Intention to Learn Cloud Computing	0.870	3.33	0.86
Cloud computing is a topic which should be offered as the university core course			
Cloud computing is a topic which should be offered as the university elective course			
Cloud computing is a topic which I should learn to make me more competitive in the job market			
Cloud computing is a topic which is relevant to my major			
Cloud computing is a topic that every should learn how to use it			

The statistical software package SPSS 25 with AMOS 25 was used to analyze the respondents' data. For Structural Equation Model (SEM), Hair, Black, Babin, and Anderson (2009) recommends a sample size of at least 200. Therefore, our sample of 435 exceeds the recommended value.

Reliability Test

A reliability test was conducted to examine the internal consistency for each of the factors. The Cronbach α values are listed in Table 2. All alpha values are greater than the recommended value of 0.70 (Nunnally, 1978). Thus, the reliability of the study factors is acceptable.

KMO and Bartlett's Test

The KMO and Bartlett's Test was conducted to assess the degree of unidimensionality of the scales. The results are shown in Table 3. The test confirmed the sampling adequacy with the value of 0.947. The Bartlett's test of sphericity showed a p-value of 0.000 for both sets of data. Thus, the null hypothesis was rejected regarding no difference between the correlation matrix and the identity matrix.

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Table 3. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.947
Bartlett's Test of Sphericity	Approx. Chi-Square	11002.483
	df	561
	Sig.	0.000

Multicollinearity test

Multicollinearity test

The variance inflation factor (VIF) is a common measure used to assess the multicollinearity between independent variables. Hair et al. (2009) recommends a VIF score below 5.0 to demonstrate that multicollinearity is not an issue among the independent variables. Table 4 lists the results of the multicollinearity test. The VIF scores range between 1.324 to 2.257 falling within the acceptable range for VIF scores.

Table 4. Multicollinearity test

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.050	.175		.284	.776		
PU	.367	.051	.347	7.139	.000	.523	1.911
PEU	-.061	.050	-.060	-1.214	.225	.501	1.996
PS	.139	.046	.134	3.021	.003	.628	1.593
PSU	.014	.054	.014	.266	.790	.461	2.169
PC	.123	.056	.115	2.184	.030	.443	2.257
NB	.189	.039	.195	4.825	.000	.755	1.324
TC	.172	.042	.190	4.138	.000	.587	1.704

a. Dependent Variable: INT

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Construct Validity Test - Factor Analysis

Confirmatory factor analysis with varimax rotation was conducted to examine the construct validity and to verify the groupings of the survey items adopted from previous studies. The results of the factor analysis confirm that the forty survey items distributed themselves into eight factors (see Table 5). The survey items which recorded a value below the suggested reliability level of 0.65 (Hair et al. 2009) were removed from the data analysis.

Table 5. Factor analysis

Constructs	**Component**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Perceive Usefulness (PU1)	.139	.296	.221	.262	.205	**.667**	.081	.145
Perceive Usefulness (PU2)	.125	.169	.122	.283	.083	**.774**	.132	.127
Perceive Usefulness (PU3)	.225	.286	.241	.163	.218	**.694**	.094	.034
Perceive Usefulness (PU4)	.199	.136	.176	.197	.220	**.681**	.051	.096
Perceived Ease of Use (PEU1)	.243	.214	.218	.110	**.724**	.240	.129	.098
Perceived Ease of Use (PEU2)	.288	.228	.218	.070	**.767**	.230	.132	.003
Perceived Ease of Use (PEU3)	.240	.164	.241	.119	**.767**	.171	.102	.017
Perceived Ease of Use (PEU4)	.147	.176	.097	.168	**.709**	.061	.177	.222
Perceived Security (PS1)	.121	.172	.211	.235	.190	.067	**.781**	.090
Perceived Security (PS2)	.155	.192	.167	.171	.138	.079	**.844**	.104
Perceived Security (PS3)	.164	.183	.275	.096	.127	.148	**.764**	.091
Perceived Speed of Access (PSA1)	.180	**.769**	.190	.178	.152	.193	.106	.115
Perceived Speed of Access (PSA2)	.203	**.775**	.288	.142	.132	.197	.098	-.002
Perceived Speed of Access (PSA3)	.189	**.773**	.160	.092	.201	.115	.192	.119
Perceived Speed of Access (PSA4)	.216	**.777**	.222	.148	.184	.199	.186	.098
Perceived Speed of Access (PSA5)	.195	**.719**	.261	.201	.170	.161	.133	.143
Perceived Cost of Usage (PCU1)	.086	.159	**.734**	.154	.138	.146	.184	.072
Perceived Cost of Usage (PCU2)	.170	.200	**.739**	.088	.163	.191	.162	.112
Perceived Cost of Usage (PCU3)	.148	.282	**.725**	.159	.180	.146	.164	.138
Perceived Cost of Usage (PCU4)	.150	.283	**.699**	.216	.132	.180	.122	.176
Perceived Cost of Usage (PCU5)	.204	.197	**.711**	.216	.204	.099	.174	.170
Normative Beliefs (NB1)	-.010	.211	.258	.179	.130	.081	-.005	**.735**
Normative Beliefs (NB2)	-.086	.038	.194	.184	.152	.057	.121	**.823**
Normative Beliefs (NB3)	-.032	.075	.027	.110	-.014	.131	.111	**.811**

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Technology Competency (TC1)	**.811**	.214	.099	.237	.152	.109	.030	-.039
Technology Competency (TC2)	**.754**	.165	.130	.088	.187	.082	.171	-.097
Technology Competency (TC3)	**.845**	.171	.157	.077	.199	.113	.092	-.019
Technology Competency (TC4)	**.855**	.145	.152	.170	.125	.174	.086	-.003
Technology Competency (TC5)	**.843**	.146	.112	.165	.155	.146	.120	.037
Intention to Learn (INT1)	.138	.101	.034	**.755**	.090	.061	.135	.183
Intention to Learn (INT2)	.106	.187	.136	**.780**	.109	.105	.082	.098
Intention to Learn (INT3)	.197	.187	.251	**.699**	.044	.275	.025	.077
Intention to Learn (INT4)	.116	.028	.154	**.678**	.048	.252	.184	.116
Intention to Learn (INT5)	.213	.186	.223	**.700**	.194	.209	.133	.120

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
The loadings are <0.65 were removed from the data analysis.

Discriminant validity test – average variance extracted

As shown in Table 6, a correlation analysis was conducted to test the relationship between each variable. The correlation between the intention to learn cloud computing (INT) and its determinants ranged from 0.397 to 0.600, indicating a high likelihood that these factors influence subjects' intention to learn cloud computing. The construct validity was also assessed by testing the discriminant validity. The discriminant validity is the extent to which the items do not correlate with other items of a different construct (Roni 2014). In order to test the discriminant validity, the average variance extracted (AVE) for all constructs were calculated to ensure that they are >0.5. The square root of AVE was also compared with the inter-construct correlations. The results in Table 6 demonstrate that the discriminant validity is supported as the square root of the constructs'
AVE was greater than the correlations of the construct with all other constructs (Fornell and Larcker 1981; Hulland 1999; Roni, 2014).

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Table 6. Correlation matrix and average variance extracted (AVE)

Constructs	Average Variance Extracted (AVE)	Square Root of AVE	PU	PEOU	PS	PSA	PCU	NB	TC	INT
PU	0.5220	0.7225	1							
PEU	0.5509	0.7422	.568**	1						
PS	0.6353	0.7971	.421**	.477**	1					
PSA	0.5820	0.7629	.589**	.573**	.506**	1				
PCU	0.5209	0.7218	.573**	.574**	.550**	.639**	1			
NB	0.6251	0.7906	.337*	.298**	.306**	.324**	.414**	1		
TC	0.6764	0.8224	.480**	.540**	.394**	.510**	.449**	.055	1	
INT	0.5233	0.7234	.600**	.436**	.456**	.485**	.528**	.397**	.446**	1

** Correlation is significant at the 0.01 level.

Common method bias

To ensure that the model is free from common method bias, which is a measurement error that threatens the validity of conclusions drawn from statistical results, Harman's single factor test was conducted. The Harman's single factor test which is the most widely used in the literature (Roni 2014) was obtained by running an un-rotated, single-factor constraint of factor analysis in SPSS statistics. As shown in Table 7, the variance explained by a single factor of 41.498% is less than the recommended 50% cut-off point (Roni 2014), indicating that the common method bias is not a major concern in this study.

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Table 7. Total variance explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Com.	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.109	41.498	41.498	14.109	41.498	41.498	4.248	12.493	12.493
2	2.932	8.624	50.122	2.932	8.624	50.122	3.949	11.613	24.107
3	2.030	5.971	56.093	2.030	5.971	56.093	3.687	10.844	34.951
4	1.610	4.736	60.830	1.610	4.736	60.830	3.445	10.133	45.084
5	1.478	4.347	65.176	1.478	4.347	65.176	2.940	8.648	53.732
6	1.291	3.798	68.974	1.291	3.798	68.974	2.770	8.147	61.879
7	1.258	3.699	72.674	1.258	3.699	72.674	2.426	7.135	69.014
8	1.011	2.973	75.647	1.011	2.973	75.647	2.255	6.633	75.647
9	.612	1.799	77.446						
10	.576	1.693	79.139						
11	.535	1.573	80.712						
12	.490	1.441	82.153						
13	.435	1.281	83.434						
14	.415	1.220	84.654						
15	.408	1.199	85.853						
16	.386	1.135	86.988						
17	.367	1.079	88.067						
18	.350	1.029	89.097						
19	.346	1.019	90.115						
20	.313	.921	91.036						
21	.294	.865	91.901						
22	.285	.839	92.741						
23	.271	.797	93.538						
24	.261	.767	94.305						
25	.246	.724	95.029						
26	.233	.685	95.714						
27	.221	.651	96.365						
28	.209	.616	96.981						
29	.202	.595	97.576						
30	.192	.566	98.142						
31	.187	.551	98.693						
32	.165	.485	99.178						
33	.149	.437	99.615						
34	.131	.385	100.000						

Extraction Method: Principal Component Analysis.

Structural equation model

SPSS AMOS 25 was utilized to evaluate the proposed research model. To test the overall goodness of fit of the proposed research model, the measures of df/Chi-

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square, Goodness of fit, Adjusted goodness of fit, Root mean square error of approximation, Comparative fit index, Tucker Lewis index, and Normed fit index were employed. Table 8 reveals that all the goodness of fit indices fall within their acceptable levels (Bentler and Bonett 1980; Hu and Bentler 1995; Tucker and Lewis 1973). This reveals that the proposed research model exhibited a good fit with the data.

Table 8. Fit indices for the models

Fit Indices	Recommended Value	Measurement Model
Chi-square (CMIN)/df	<=3.00	1.282
Goodness-of-fit (GFI)	>=0.90	0.999
Adjusted goodness-of-fit (AGFI)	>=0.80	0.999
Normed fit index (NFI)	>=0.90	0.997
Tucker Lewis Index (TLI)	>=0.90	0.995
Comparative fit index (CFI)	>=0.93	0.999
Root Mean Square Error of Approximation (RMSEA)	<=0.06	0.025

Hypothesis testing

The results of hypothesis testing are shown in Table 9. Properties of the causal paths including standardized path coefficients are presented in Figure 4.

Table 9. Hypothesis testing and results

H#	Hypothesis Testing			Standardized estimate (β)	Critical Ratio	p-value
1	Technology Competency	→	Perceived Ease of Use of Cloud Computing	1.008	11.102	***
2	Perceived Ease of Use of Cloud Computing	→	Perceived Usefulness of Cloud Computing	0.923	14.371	***

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Table 9. Hypothesis testing and results-continue

H#	Hypothesis Testing		Standardized estimate (β)	Critical Ratio	p-value
3	Perceived Ease of Use of Cloud Computing	→ Intention to Learn Cloud Computing	-0.390	-2.795	0.005
4	Perceived Usefulness of Cloud Computing	→ Intention to Learn Cloud Computing	0.054	0.406	0.685
5	Perceived Security of Cloud Computing	→ Intention to Learn Cloud Computing	0.241	4.000	***
6	Perceived Speed of Access of Cloud Computing	→ Intention to Learn Cloud Computing	0.297	2.908	0.004
7	Perceived Cost of Usage of Cloud Computing	→ Intention to Learn Cloud Computing	0.350	3.643	***
8	Normative Beliefs	→ Intention to Learn Cloud Computing	0.176	4.015	***

*** indicates significance level < 0.001

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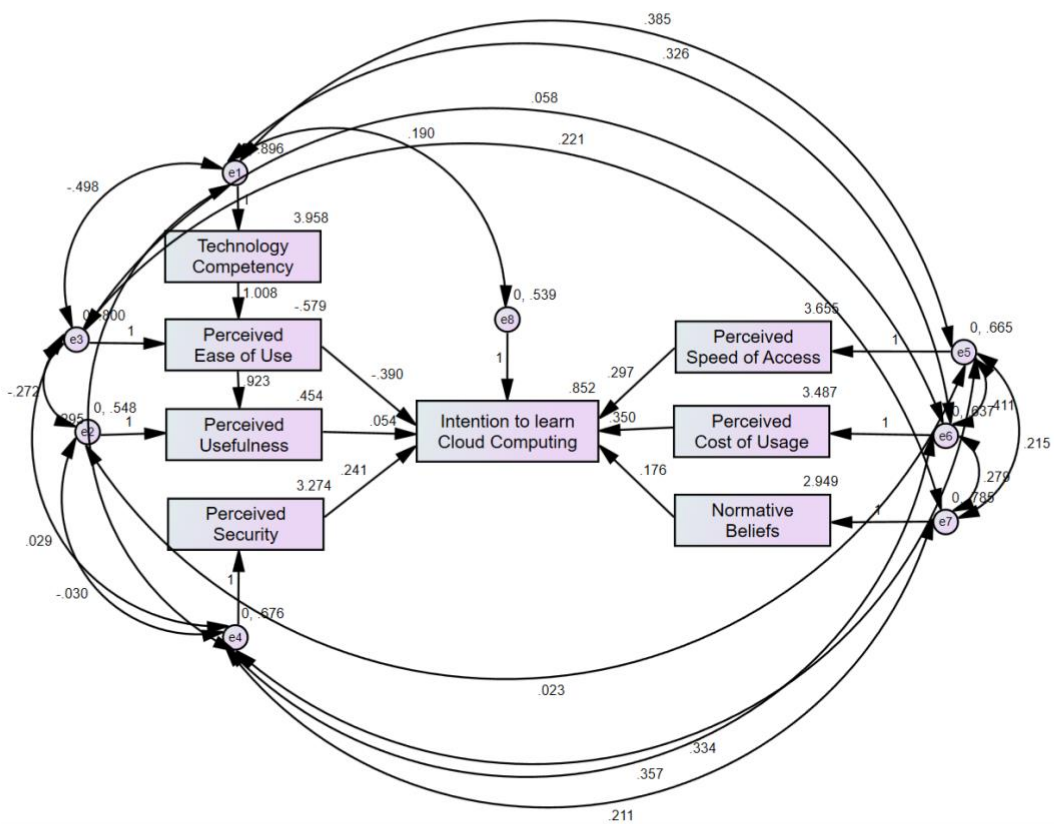
Figure 4. Structural equation model path analysis



For hypothesis H1, the result demonstrates a significant relationship between subjects' technology competency and their perceived ease of use of cloud computing (β = 1.008, p-value < 0.001). This result is counter to the findings of Furner (2013) who found no relationship between the closely related factor of computer self-efficacy and intention. Nevertheless, this study's finding indicates that subjects who consider themselves confident with using computers also find it easy to use cloud computing. The result conforms to a prior study which reported that the higher the perceived level of technology competency that subjects have, the more likely that they will find the technology easy to use (Venkatesh and Davis, 1996).

The result of hypothesis H2 confirms the relationship between perceived ease of use and perceived usefulness (β = 0.923, p-value < 0.001). The finding is in line with the study conducted by Davis et al. (1989), which indicates that the perceived

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ease of use can positively influence subjects' perceived usefulness. The results reveal that if students find that cloud computing is easy to use, they will tend to agree that this topic is beneficial for them to learn how to use it.

Hypothesis H3 examines the relationship between perceived ease of use of cloud computing and students' intention to learn cloud computing. The results reveal a significant negative relationship between these two constructs (β = -0.390, p-value = 0.005). This result confirms the findings of some prior studies that found a significant relationship between perceived ease of use and intention (e.g., Dasgupta, Paul, and Fuloria 2011; Sripalawat, Thongmak, and Ngramyarn 2011) but contradicts other previous studies that reported no significant relationship between perceived ease of use and intention (e.g., Koenig-Lewis, Palmer, and Moll 2010; Liébana-Cabanillas, Alonso-Dos-Santos, Soto-Fuentes, and Valderrama-Palma 2016). It should be noted that the data appear to suggest that the higher the perceived ease of use is the less likely students will have the intention to learn cloud computing. This may be because if students believe the cloud computing is quite easy to use, they will tend to believe that they do not need to learn about it.

Regarding hypothesis H4, it is quite interesting to find that the factor perceived usefulness of cloud computing does not have a significant influence on students' intention to learn cloud computing (β = 0.054, p-value = 0.685). The result contradicts TAM and other previous studies (e.g., Hanafizadeh, Keating, and Khedmatgozar 2014; Moqbel and Bartelt 2015; Püschel, Mazzon, and Hernandez 2010). However, this finding is similar to the results of a study by Lucia-palacios, Pérez-lópez, and Polo-redondo (2016) who reported that perceived usefulness is not a significant factor in the adoption of cloud computing in a model that includes inertia. It appears that whether students believe that cloud computing is useful or not, it does not impact their intention to learn cloud computing. This could be due to the fact that students may know that businesses are increasingly turning to the cloud to support their IT function. Thus, it is irrelevant whether they find this technology to be useful or not as they will have to learn to use cloud computing if they go to work for a business that employs cloud computing.

Hypothesis H5 reveals the relationship between the perceived security of cloud computing and students' intention to learn cloud computing (β = 0.241, p-value < 0.001). This result validates prior studies that perceived security plays an important role in technology acceptance (e.g., Alalwan, Dwivedi, and Rana 2017; Bhatt 2016; Svilar and Zupančič 2016). It is apparent that students are willing to learn cloud computing if they believe this technology is secure.

For hypothesis H6, the result confirms that there is a significant relationship between the perceived speed of access of cloud computing and students' intention to learn cloud computing (β = 0.297, p-value = 0.004). This finding is in line with results uncovered by Willet and Von Solms (2014) in a survey study they administered to higher education institutions in South Africa. Thus, it is quite

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obvious that the speed of access should be considered a crucial feature of cloud computing since slow access would delay students' completion of their work. Students who view cloud computing as having good speed of access are more likely to want to learn about this technology and thus willing to accept it as part of their curriculum.

The result demonstrates support for H7. The perceived cost of usage of cloud computing is also positively related to students' intention to learn cloud computing ($\beta = 0.350$, p-value < 0.001). This result matches the result found by Tripathi (2019) although they uncovered a negative relationship between perceived cost and intention. This finding indicates that students who perceive the cost of cloud computing as low are willing to learn more about the cloud computing technology and are likely to accept it as part of their core curriculum.

Lastly, hypothesis H8 reports a positive relationship between normative beliefs and students' intention to learn cloud computing ($\beta = 0.176$, p-value < 0.001).

This finding conforms to the results in a prior study by Bock, Zmud, Kim, and Lee (2005). Since students usually need to share data among friends and family members, they are more likely to be heavily influenced by the experiences of these people.

Study Implications

This study contributes to the current information systems theory on cloud computing by proposing and empirically testing factors that contribute to behavioral intention toward cloud computing. This study extended the TAM to include the factors of technology competency, perceived security, perceived speed of access, perceived cost of usage, and normative beliefs. All the model factors with the exception of TAM's perceived usefulness were found to be statistically significant contributors to students' intention to learn cloud computing.

Perceived usefulness, one of the TAM's original factors contributing to information systems behavioral intention, was not found to have a significant impact on the intention to learn cloud computing technology. Many universities nowadays have adopted cloud technology as the storage for students to store and share data with faculty and friends. So, regardless of whether students perceive this technology as useful or not, they are aware that businesses are increasing their reliance on cloud computing. Thus, the perceived usefulness of cloud computing no longer plays a significant role in determining whether students are willing to learn cloud computing.

Both practical and scientific insights to colleges and universities that are considering adding a cloud computing component to their curriculum and to the cloud computing literature are provided by this study. This study contributes to the current literature by examining cloud computing from a different perspective. Many prior cloud computing studies have focused on organizational adoption of cloud

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computing by both commercial and academic organizations as well as by individuals. Very few studies have focused on the students' perspective and examined which factors could influence them to learn cloud computing.

This study's findings should also assist colleges and universities that are considering adding cloud computing to their curriculum. By knowing what students view as important factors in learning about cloud computing, these academic institutions can focus on those factors to implement a smooth integration of cloud computing into the existing curriculum.

CONCLUSION

This study focused on the factors that influence students' intention to learn cloud computing as part of their curriculum. The proposed research model extended the TAM to include the following factors: technology competency, perceived security, perceived speed of access, perceived cost of usage, and normative beliefs. The proposed model was evaluated using structural equation modeling with SPSS and AMOS 25. The results revealed the factors that students find influential in their intention to learn cloud computing.

The results in this study reveal that six out of the seven proposed factors play an important role in influencing students' intention to learn cloud computing either through an indirect or direct relationship. The results of the data analysis reveal support for hypotheses H1-H3 and H5-H8 (see Table 6). Hypothesis H4 was not supported. Overall, the independent variables in the research model explain 75.647 percent of the variability in subjects' intention to learn cloud computing.

The factors that were found to be influential with support results are technology competency, perceived ease of use, perceive speed of access, perceived cost of usage, and normative beliefs. Interestingly, this study does not find a significant relationship between perceived usefulness and students' intention to learn cloud computing. This result reveals that regardless of whether students perceive cloud computing as a technology that will be beneficial to them, they will be generally open to learning this cloud computing technology since businesses are increasingly adopting cloud computing.

The results in this study reveal that students with a higher competence in technology will find cloud computing easier to use than those who have lower technology competency and thus this factor will influence their intention to learn this technology. In addition, if students believe that cloud computing is secure, they will be more like to want to learn this technology.

Findings in this study also demonstrate that the speed of access and the cost of using cloud storage are also crucial factors that can influence students' intention to learn cloud computing. Students now prefer technology that allows them to get the thing they want in a timely manner.

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In addition, it does not matter how great a service a new technology can render, it will be useless if students cannot afford the cost of using it. Students will be more willing to learn cloud computing technology if they perceive that it does not cost them much to use the technology.

Based on the findings, normative beliefs also positively influence students' intentions to learn cloud computing. This is quite understandable as students will need to share data with their family members and friends. The attitudes of people around them should influence their intention to learn the cloud computing technology.

As in most empirical studies, there is an inherent limitation in this research. The sample in this research was limited to subjects from one university. Although there was an attempt to gather the data from a variety of courses in the university, future research should be conducted at multiple universities. Further research should also consider expanding demographics to include students in various countries.

In addition, a future study could investigate in more detail which feature of cloud computing help increase students' effectiveness and efficiency in the classroom.

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