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Factors Affecting Cloud Computing Adoption in a Developing Country– Ghana: Using Extended Unified Theory of Acceptance and Use Of Technology (UTAUT2) Model

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Abstract- *Cloud computing is one of the most discussed topics in recent years among enterprise Information Systems (IS). Many IS professionals now consider cloud technology to be the best solution to improve the growth of businesses in every sector. Today, many organisations in developing countries are struggling to muddle through the rapid market variations. Organisations find it difficult to meet customer expectations alongside with growing business requirements. Despite the many advantages that organisations may benefit from cloud computing, the adoption rate is however relatively low in some developing countries. However, organisations in the developing countries need to benefit from cloud technology in order to realize increased productivity and enhanced efficiency in businesses operations. This has been a major hurdle for organisations to overcome, which therefore requires great attention. An exploratory research was initially conducted to identify an appropriate theoretical framework for technology adoption testing and validation. Afterwards, a quantitative survey was employed to understand the intentions of organisations towards the adoption and usage of cloud computing technology regarding the framework used. The relationship between organisations' intention of using cloud computing and the actual behaviour was tested; a Linear Multiple Regression method was adopted to analyse the responses. Moreover, Pearsons correlation analysis was executed to find relationship between variables. The findings discovered facilitating condition, habit, performance expectancy, and price value were positive significant factors influencing cloud technology adoption in Ghana. On the contrary, effort expectancy, hedonic motivation, and social influence negatively influence cloud technology adoption in Ghana, whereas, security was however insignificant. For an effective adoption of the cloud services, this study recommends extensive awareness campaigns to targeted potential cloud computing users in regard to cloud data privacy. Individuals should be made known the security policies and measures in place. Furthermore, individuals should be educated on how they could be security conscious in order to protect their sensitive information against cyber theft. Cloud users should always be mindful of the information they provide online, the device they use, and the web sites they visit in order to prevent their information from reaching cybercriminals.*

Keywords: Cloud Computing, Cybercriminals, Exploratory, Information Systems, Privacy, Security,

1. INTRODUCTION

1.1 Background Study

Cloud computing is one of the most discussed topics in recent years among enterprise Information Systems (IS). Many IS professionals now consider cloud technology to be the best solution to improve the growth of businesses in every sector. A research organized by *Alsanea and Barth (2014) shows that* 85.80% of their respondents support the adoption of cloud computing technology, 97.63% perceived its usefulness, and 95.26%, perceived the service quality and security as significant factors. Cloud Security Alliance (CSA) acknowledged the rapid increasing rate of cloud technology adoption as the most suitable solution to organisations for effective data management due to its large number of benefits such as flexibility, scalability, and affordability (Aharony, 2015), which increases efficiency for all kinds of businesses (CSA, 2011). Cloud computing technology also provides more opportunities and gives business advantages to both small and medium enterprise. This is because it allows gradual implementation, which requires minimal initial investment (Bildosola et al., 2015) as confirmed by scholars and research organisations such as the International Data Corporation (IDC) and Cisco Global Cloud Index (GCI) (IDC, 2015; GCI, 2015; *Alsanea & Barth, 2014)*. According to Masrom and Rahimli (2015), a major feature that boosts the adoption of cloud computing by many organisations is its enablement of smoothly data exchange between diverse systems without encountering much challenge with the controlling infrastructure of the data. This provides ease for small, medium, and large sized organisations worldwide to expand their businesses, increase productivity and efficiency with less capital expenditure.

1.1 Problem Statement

Today, many organisations in developing countries are struggling to muddle through the rapid market variations. Organisations find it difficult to meet customer expectations alongside with growing business requirements (Omar et al., 2015). Despite the many advantages that organisations may benefit from cloud computing (GCI, 2015; IDC, 2015; *Alsanea & Barth, 2014*), the adoption rate is however relatively low in some developing countries (U.S. Department of Commerce, 2016; Senarathna et al., 2016; Omar et al., 2015; Alismaili et al., 2015). However, organisations in the developing countries need to benefit from cloud technology in order to realize increased productivity and enhanced efficiency in businesses operations. This has been a major hurdle for organisations to overcome, which therefore requires great attention.

1.2. Research Questions

The following research questions were raised for the achievement of the study objectives:

i. RQ1. To what extent do technological factors affects acceptance of cloud technology?

ii. RQ2. To what extent do organizational factors affects acceptance of cloud technology?

iii. RQ3. To what extent do environmental factors affects acceptance of cloud technology?

1.4 Research Hypotheses

To help us address our questions appropriately, the following hypotheses were formulated based on the constructs of the adopted theoretical framework:

H_1: performance expectancy (PE), facilitating condition (FC), price value (PV), and security (SE) will significantly impact the behavioural intention (BI) of cloud computing adoption.

H_2: effort expectancy (EE), hedonic motivation (HM), and habit (HB) will significantly influence the behavioural intention (BI) of cloud computing adoption.

H_3: social influence (SI) will significantly impact the BI of cloud computing adoption.

H_4: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), hedonic motivation (HM), price value (PV), habit (HB), and security (SE) will significantly have impact on behavioural intention (BI) of cloud computing adoption.

H_5: behavioural intention (BI), price value (PV), and facilitating condition (FC) have significant on UB of cloud computing adoption.

1.3. Research Objectives

The objective of this research is to provide deeper research into each of the adoption factors (technological, environmental and organizational), using the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). This will enable us determine factors influencing cloud adoption in Ghana, and hence provide guidelines for organisations planning to adopt the cloud technology.

1.4. Significance

The study in a long run will help the providers of cloud technology services and policymakers in developing strategic solutions to address issues contributing to the relatively low adoption of cloud technologies in Ghana. Moreover, it will help the organizational leaders to understand how cloud computing would be a beneficial to their businesses in this agile world. Finally, the result of this research would create a platform for advance investigation.

2. LITERATURE REVIEW

2.1 Features of Cloud Computing

NIST (2011) classified the features of cloud computing into three different categories. That is, five vital characteristics, three service models, and four deployment models.

1) 2.1.1 Cloud characteristics

NIST identified cloud computing characteristics as i) broad network access, ii) rapid elasticity, iii) on-demand self-service, iv) measured service, and v) resource pooling.

Broad network access could be described as the ability of the cloud user to use standard mechanisms such as mobile phones, workstations, and laptops in accessing any available cloud infrastructure in the form of promoting heterogeneity **(**Zissis & Lekkas, 2012; Lee, 2015; Gutierrez, 2015**)**.

Rapid elasticity describes how quickly and automatically the pooled resources on the cloud systems are released to appropriate customers when demanded in any quantity at any time (Lee, 2015; Gutierrez, 2015).

On-demand self-service enables cloud computing consumers to automatically and separately adjust system functionalities without the service providers' interference. This functionalities may include and server time and network storage (Lee, 2015; Gutierrez et al., 2015).

Measured service is the capability of monitoring, controlling, reporting, and providing transparency of cloud service utilization to both provider and consumer automatically (Lee, 2015; Gutierrez, 2015).

Resource pooling involves collective cloud resources deployed to serve various users who are connected to the cloud platform. This promotes mechanisms such remote access and multi-tenancy (the provision of web access to multiple users or customer to a single instance of application). This is the means of assigning physical and virtual resources (which include memory, storage, and processing) to cloud customers. This can be done dynamically based on the customers' demand without having any control of the location of the resource (Lee, 2015; Gutierrez, 2015; Zissis & Lekkas, 2012).

The services of cloud technology are divided under three models namely: Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS).

Software as a Service (SaaS) permits cloud customers to utilize available pooled resources hosted as cloud infrastructure whereby using different client devices via web browsers or program interfaces (Lee, 2015; Gutierrez, 2015).

Platform as a Service (PaaS) refers to permissions granted to cloud users such as programmers and web application developers regarding deployment access to enable them deploy the applications they have developed or acquired unto the cloud platform (Gutierrez, 2015). This enables the user to only get access to some configuration settings related to the application been deployed, however, does not manage the infrastructure functionalities like the servers, operating systems, and network storage.

Infrastructure as a Service (IaaS) is where the cloud consumer is granted partial accessibility to control cloud infrastructures such as operating systems, host firewalls, deployed applications, and other networking modules (Lee, 2015, Gutierrez; 2015).

2) 2.1.3 Deployment models

NIST outlined four basic models in which cloud systems can be deployed. According to Sen (2013), these deployment models are based on who provides and who accesses the service. The deployment is categorized into private, public, community, and hybrid clouds models.

Private clouds are processes where specific organisations are provided with the services they require and are therefore treated as sole managers and or owners of the allotted instances. The organisation may choose to handle the management of the service by themselves or assign it to a third party organisation (Gutierrez, 2015; Lee, 2015; Sen, 2013; Williams, 2012). These models are usually managed and hosted by the organisation itself or an employed third-party support, however, accessed by trusted customers.

Public clouds unlike the private are services opened to general unrestricted users. They mostly owned and managed by the services providers (Lee, 2015, Gutierrez, 2015; Sen, 2013; Williams, 2012). The hosting is always done off the organisations' premises and managed by third-party provider. Accessibility is open to untrusted customers.

Community cloud services on the other hand are offered to collective organisations with related mission of supporting community with mutual concerns. In most cases, the organisations choose to manage their own services, therefore, hosting it at a vantage premise accessible to all (Lee, 2015; Gutierrez, 2015; Sen, 2013; Williams, 2012).

Hybrid cloud is the process of deployment where two or more of the above stated service models are combined to form a single model, therefore, making it quite complex. For example, private cloud deployed for the central bank accessible and manipulated by community cloud for other banks (Gutierrez, 2015; Lee, 2015; Sen, 2013; Williams, 2012). These types of cloud models can be managed by the organisation itself or an employed third-party support. The hosting is always done off the organisations' premise.

According to Sen (2013), the migrating from the traditional non-cloud environments to cloud environments offers a new business opportunity where acquiring of information and communication technologies are centred on "on-demand payment". The cloud technology offers equal opportunities of business advantage to both small and medium size enterprises by providing a gradual implementation process that requires minimal initial investment to organisations, hence, the massive cloud adoption trend (Bildosola et al., 2015).

2.4 Threats on the Cloud

Cloud technology is suffering numerous threats since the emergent of the technology (Zhou et al., 2012). These threats usually render the privacy and confidentiality of data transmitted via the cloud networks, therefore, compromising its integrity. Many famous researchers contradicted cloud evolvement base on these threats. Armbrust and Shimba for instance outlined technical, policy and organizational obstacles as threats to cloud services (Shimba, 2010; Armbrust et al., 2010). Likewise, Zhou et al. (2012), emphasized **technical issues, security in the cloud, data prone to attack, outages,** and **slow speeds as** cloud inhibits. Similarly, Maslin and Ailar (2015) highlighted loss of data, failure in compliance, and privacy and security concerns as hindrances to cloud adoption.

Sen (2013) in his study of exploring cloud security stated that as technology invention increases, threats are being diversified as well to counteract security measures implemented. He observed emerging trend of cloud security threats such as mobile device attacks, mash-up authorization, social networking attacks, increased authentication demands, denial of service attacks, side channel attacks, insider and organized crime threat, cost-effective defence of availability, and cheap data and data analysis threat. Table 2-3 discusses these threats and the mechanism they use in manipulating data on the cloud as discussed by Sen (2013).

Table 2-3. Cloud Security Threat.

Threat	***Mechanism***
Mobile device attacks	*This involves process of stealing information from cloud subscribers through their mobile devices due to lack of enabled security features, updated antimalware, antivirus or full disk encryption technologies (Sinjilawi et al., 2014). This is normally achieved through the execution of malicious codes such as worms, spyware, or viruses upon connection to the internet.*
Mash-up authorization	*Using malicious applications running in third-party applications to steal sensitive data after the user has rightfully connected to the main application (Ko et al, 2015).*
Social networking attacks	*Phishing out information through the use of advanced social engineering after setting up identity to gain trust.*
Increased authentication demands	*The use threats mechanisms such as phishing and man-in-the-middle to steal users access credentials.*
Denial of service attacks	*Distributed flooding of networks with excessive traffic to consume the available bandwidth and also cause function failure to some critical system components to prevent data availability (Sinjilawi, Mohammad, and Emad , 2014).*
Side channel attacks	*The use of virtualization platforms to leakage sensitive information such encryption keys of virtual machines (Sen, 2013).*
Insider and organized crime threat	*This is where attackers gain access through the use of an insider or a person with legal access to customer information.*
Cost-effective defense of availability	*A cyber-attack with the intention of degrading the trust of any cloud infrastructure through sabotaging to increase losses in productivity.*
Cheap data analysis	*The pulling of customer's information by attackers as cheap data mining techniques are used to analyse huge customers data sets for advertisement purposes (Sen, 2013).*

Providentially, these threats are being addressed by cloud stakeholders such as the academia, data communication security organisations, and cloud service providers. The major areas at which the security of data can be jeopardized are seriously explored to help achieve substantial trust regarding to cloud data protection. This has contributed to the establishment of cloud security organisations to strictly enforce standards, policies, and rules governing information to make cloud computing gain the required trust of data security in the context of confidentiality, integrity and availability (CIA). Evidentially, the following sections discuss the trend of security measure being undertaken for the achievement of cloud data privacy and security.

2.5 Cloud Data Privacy Issues

Privacy or security is very paramount factors as far as data and data transmission is concerned. The need to keep data or information secure and confidential till it reaches its final destination or the authorized user is very important. During the past decade, it has been a major concern of most researchers to maximize cloud data security.

Cloud Security Alliance (CSA) in alliance with Trust Computing Group (TCG), outlined six major components as critical areas of focus about data security where substantial attention is required in the cloud hence provided security mechanisms (TCG's White Paper, 2010) as shown in Figure 2-1. The areas of data where security is critical include the operating systems, databases, networks, resource scheduling, memory management, transaction load balancing, virtualization, and concurrency control (Sen, 2013). Table 2-4 discusses the components and the mechanisms put in place by TCG.

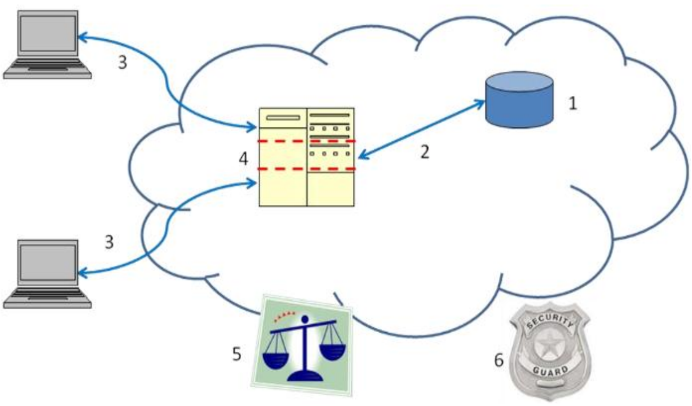

Figure 2-1. Components of data that requires security and protection.

Table 2-4. Components and their security mechanisms.

Components	*Description*	*Mechanism*
1) Data at rest	*This involves data stored in Databases and storage devices*	*Self-encrypting hard drives have been developed having TCG's Trusted Storage standards with automated encryption to achieved cryptographic encryption for data at storage.*
2) Data in transit	*This involves data been transmitted across networks.*	*The use of techniques such as encryption, authentication, integrity protection, and protocols to ensure data is not modified till its finest destination.*
3) Authentication	*This involves software, hardware and data.*	*the process of authenticating both software and hardware using a Trusted Platform Module (TPM) developed by TCG.*
4) Separation between customers	*This involves user processes and virtualization.*	*The use of techniques and mechanisms to provide Trusted Network Connection (TNC) architecture and hardware-based verification. Thus, the use of Virtual Machines (VMs) to separate customers for strong network separation and security.*
5) Cloud legal and regulatory issues	*This involves legal policies that govern both the cloud provider and the subscriber.*	*Data security policies and practices such data retention and destruction, auditing, data security and export, legal discovery, and compliance of the cloud provider needs to be reviewed to ensure adequate security.*
6) Incident response	*Availability and notification.*	*The ability of a cloud provider to notify the users about incidence on real-time basis.*

As part of finding security measures to counteract the threat and vulnerabilities of data in the cloud, CSA has establish a global cloud vulnerabilities working group in May 2013, commissioned to study the likely vulnerabilities in cloud computing, educate the public and recommend the best practices, as well as develop tools and standards to overcome such vulnerabilities (CSA homepage).

Moreover, in December 2015, a mechanism known as Cloud Trust Protocol (CTP) has been develop to help cloud subscribers evaluate the security measure of cloud provider's platform they intend to use. The CTP provides vital information such as the cloud provider's compliance, privacy, integrity, and operational security history by therefore, generating evidence-based confidence between both the cloud provider and the consumer and also assure consumers the security of their sensitive data.

In addition, a Cloud Data Governance Working Group has been established since June 2015, whose objective is designing of common set of principles regarding the evolving technologies, proposing data framework, developing data protection and data governance leadership materials to meet new data security requirements across the spheres of cloud computing (CDGWG homepage, n.d.).

Besides, achieving data security in the cloud does not focus on data protection only. However, the need of established standard development organisations and cloud data policy makers to provide laydown standards and policies for cloud technology stakeholders such as the hardware manufacturers, software developers, and cloud infrastructure users to adhere. Therefore, the following section discusses some of the standard development organisations regarding data security and their roles.

3. RESEARCH METHODOLOGY

3.1 Research Design

An exploratory research was initially conducted to identify an appropriate theoretical framework for technology adoption testing and validation. Afterwards, a quantitative survey was employed to understand the intentions of organisations towards the adoption and usage of cloud computing technology regarding the framework used.

3.2 Research Approach

As research method involves the techniques and instruments used in collecting data for the study (Bryman and Bell, 2015), the study conducted a cross-sectional survey where questionnaires were distributed to targeted respondents within different organizational sectors in order to quantitatively describe relationship among the variables and also to provide generalization of sample to the population.

3.3 Population Sample

The study adopted convenience sampling which enabled samples to be chosen based on availability and accessibility (Yilmaz et al., 2015). Convenience sampling was used because the study aimed at getting respondents across the country. The study selected middle and top level managers from different industry sectors across the country, who are involved in decision making regarding both IT and business strategies. The sample was chosen because they are involved in decision making in their organisations, hence, can provide useful information regarding cloud technology usage.

3.4 Data Collection and Sampling Frame

The questionnaires were self-administered specifically to employees of selected organisations in five regional capitals of Ghana. Moreover, the questionnaires were given to postgraduate students in some selected universities who were offering distance and sandwich courses and fall within the targeted sample. The students selected were managers with several organisations and at various levels of management. These students were contacted at their study centres (at universities where they study) at their respective regional capitals. This, therefore, provides ease of access in collecting data that represent organisations across the country. In total, we administered 225 questionnaires, out of which 194 (86%) useful responses were obtained.

3.5 Research Instrument

A 70 item questionnaire instrument was designed for the survey. The items represented independent and dependent variables used in the survey. The instrument has two sessions. The first session gathers information about the respondents demographic data – background data such as gender, age, educational level, industry, and basic knowledge about cloud computing, while the second part asks questions about the variables of the study base on a five point Likert scales ranges between 1 (strongly disagree) and 5 (strongly agree).

Table 3-1. Instrument Reliability Coefficients.

Constructs	*No. of Items*	*Reliability (Cronbach Alpha)*
Performance Expectancy(PE)	*7*	*0.78*
Effort Expectancy(EE)	*9*	*0.54*
Social influence(SI)	*7*	*0.69*
Facilitation Condition(FC)	*7*	*0.62*
Hedonic Motivation(HM)	*3*	*0.75*

Price Value(PV)	*7*	*0.70*
Security (SE)	*4*	*0.77*
Habit(HB)	*5*	*0.82*
Behavioral Intention (BI)	*4*	*0.74*

As shown in the Cronbach alpha reliability test, 6 out of the 9 constructs proved reliable and therefore, acceptable. Social influence and facilitating condition constructs had alpha values of 0.69 and 0.62 respectively. Although their reliability values are less than 0.70, they are accepted for this study since their values are relatively close to 0.70. However, effort expectancy's 0.54 could probably be because it has many items on the construct, however, accepted in this research.

3.6 Data Analysis

In our analysis, we used the Statistical Package for Social Sciences (SPSS) software.

The relationship between organisations' intention of using cloud computing and the actual behaviour was tested; a Linear Regression (Multiple regression) method was adopted to analyse the responses. Moreover, Pearsons correlation analysis was executed to find relationship between variables (dependent and independent) to test how best they correlate. This could be termed as goodness of fit (Adjusted R Square) (Li, 2013).

4. RESULTS ANALYSIS AND DISCUSSION

4.0.1 Characteristics of the Respondents (Demographic Data)

A total of 194 responses were received. According to the demographic analysis, 147 (75.8%) of the respondents are male, while 47 (24.2%) are female, 100 (51.5%) are involved in IT decision making in their organisations, while 94 (48.5%) involved in business strategies. Table 4-1 shows the demographic data of our respondents.

Table 4-2: Respondents Demographic Data.

Demography	*Frequency*	*Percent*
Gender		
Male	*147*	*75.8*
Female	*47*	*24.2*
Age Group (in years)		
18-25	*8*	*4.1*
26-35	*123*	*63.4*
36-45	*45*	*23.2*
46-55	*17*	*8.8*
56-65	*1*	*.5*
Education		
GSE Level	*5*	*2.6*
High School	*3*	*1.5*
Undergraduate	*115*	*59.3*
Masters	*39*	*20.1*
Doctorate	*4*	*2.1*
Professional	*13*	*6.7*
Other	*15*	*7.7*
Work Experience (in years)		
0 – 2	*24*	*12.4*
3 – 5	*77*	*39.7*
6 – 10	*52*	*26.8*
11 – 20	*33*	*17.0*
21 and above	*8*	*4.1*

Data collected shows 62.3% of the respondents have basic knowledge about cloud computing, 21.1% have no knowledge at all, while 16.5% remain neutral. The data also reveals that 113 (58.2%) of the respondent organisations are already using cloud services, while 81 (41.8%) are yet to. Table 4-2 shows the industrial information of the respondents as well as their basic knowledge in regard to cloud computing technology.

Table 4-3: Respondents Organisational Data

Demography	*Frequency*	*Percent*
Industry		
Financial	*15*	*7.7*
Education	*60*	*30.9*
Media and Communication	*6*	*3.1*
Manufacturing	*8*	*4.1*
Healthcare	*36*	*18.6*
Information Technology	*11*	*5.7*
Public Service	*31*	*16.0*
Other	*27*	*13.9*
Part of IT Decision Making?		
Yes	*100*	*51.5*
No	*94*	*48.5*
Already Using Cloud Service?		
Yes	*113*	*58.2*
No	*81*	*41.8*
Type of Cloud Service Use - SaaS Use		
Yes	*77*	*39.7*
No	*117*	*60.3*
Type of Cloud Service Use - PaaS Use		
Yes	*33*	*17.0*
No	*161*	*83.0*
Type of Cloud Service Use - IaaS Use		
Yes	*15*	*7.7*
No	*179*	*92.3*
Has knowledge about Cloud Computing		
Yes	*121*	*62.3*
No	*41*	*21.1*
Neutral	*32*	*16.5*

N = 194

4.1 Test of Hypotheses

Regression analysis was performed base on the adopted framework (UTAUT2 - modified). This involves dependent and independent variables (outcomes and predictors). The study explored the major contributing elements affecting organisations that intend to use cloud computing technology in the context of the TOE factors. Afterwards, the results achieved for the BI was compared to the actual use behaviour. Five different analyses were performed to find the relationship among the predictor and outcome variables.

Initially, three separate analysis were run to investigate the effects of the TOE factors (thus, Technological – performance expectance (PE), facilitating conditions (FC), price value (PV), and Security (SE); Organizational – effort expectancy (EE), hedonic motivation (HM), and habit (HB); Environmental – social influence (SI)) on behavioural intention (BI). Moreover, all the independent variables (constructs) were analysed against the dependent variable, thus behavioural intention (BI). Finally, a comparism examination was conducted to find the effects of behavioural intention (BI) on the actual use behaviour (UB).

As an assumption for conducting regression analysis, the correlation between variables must be examined. Linear regression assumes that all variables have normal distributions (Osborne & Waters, 2002; Pallant, 2010), indicating normal distribution of errors with estimated normal histogram curve plotting of the residuals values. See Appendix B for normal distribution curves.

4.1.1 Effects of Technological Factors on BI

The research question one assessed the technological influence of on cloud computing adoption. Hypothesis under this research question argued that performance expectancy, price value, facilitating condition, and data security will positively and significantly influence organisations behavioural intention to adopt cloud computing technology. In hypothesis H1, we tested the significance of the predictors (PE, PV, FC, and SE) on the depend variable (BI); in the β_0 was introduced as a constant; while β_1 to β_4 signified the regression coefficients (slope parameter). The variable ε was introduced to represent any other factor that might influence the intention of the organisations in cloud adoption. The regression model to be tested is represented in H1. The logit model for multiple regression analysis was specified as follows:

$$BI = \beta_0 + \beta_1 PE + \beta_2 PV + \beta_3 FC + \beta_4 SE + \varepsilon \text{ ....} H_1$$

H_1: PE, PV, FC, and SE have significant influence on BI of cloud computing adoption.

Multiple linear regression was conducted on BI. The predictor variables (PE, PV, FC, and SE) were measured to identify how the variance in BI is proportionally explained by the predictors. The mean and standard deviation of the predictors were interpreted by the descriptive statistics as: PE (*N* = 194; M = 3.74; *SD* =.73); FC (*N* = 194; *M* = 3.50; *SD* = .62); PV (*N* = 194; *M* = 3.40; *SD* = .71); SE (*N* = 194; *M* = 3.79; *SD* = .77); and BI (*N* = 194; *M* = 3.74; *SD* = .74).

According to Gay and Airasian (2000), in order to find relationship among variables, it is important to run simple correlation analysis. Pearson analysis can be used to identify how the independent variables correlate individually to the dependent variable; thus, how PE, FC, PV, and SE correlate to BI. In the regression models, we used the predictors to help us provide a further accurate likelihood relationship between the independent (PE, FC, PV, SE) and dependent (BI) variables. This helps the selected independent variables in determining and also explaining the amount of irregularities or variations in the dependent variable. After the test, it was discovered that a strong correlation exist among the predictors and the dependent variable. The values are as follows: PE (r = .534, p < 0.01), FC (r = .578, p < 0.001), PV (r = .464, p < 0.001), and SE (r = .481, p < 0.001).

The results indicated that the predictors (PE, FC, PV, and SE) explained 68% of the the dependent variable's (BI) variation. The summary model results are presented in Table 4-3; meaning, the remaining 32% could be described by other causes not considered in our study.

Table 4-4. Model Summary (BI) of Regression on Technological factors.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.680[a]	.462	.451	.54634

a. Predictors: (Constant), SE, PV, FC, PE

b. Dependent Variable: BI

The significance of test statistic indicates a value (F (4, 189**)** = 40.578; p < 0.001) as shown in Table 4-4. This indicates that hypothesis H1 is supported and is therefore accepted.

Table 4-5. ANOVA for Regression of BI on Technological factors.

ANOVA[b]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	48.449	4	12.112	40.578	.000[a]
	Residual	56.415	189	.298		
	Total	104.863	193			

a. Predictors: (Constant), SE, PV, FC, PE

b. Dependent Variable: BI

The results of the multiple regression indicated that the independent variables (PE, FC, and PV) affects BI at significance level of p < 0.01. However, SE was not significant as illustrated in Table 4-5. The standardized estimate (b) provided the following absolute values as arranged from largest to smallest: FC (b = .435, t = 5.675, p < 0.001), PE (b = .269, t=3.540, p<0.01), PV(b=.199, t=3.106, p< 0.01) and SE(b= .023, t =.295, p = n.s).

Table 4-6. Coefficients for Regression Model of technological factors on BI.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Beta	Beta	t	Sig.
1	(Constant)	.380	.268		1.421	.157
	PE	.269	.076	.286	3.540	.001
	FC	.435	.077	.363	5.675	.000
	PV	.199	.064	.190	3.106	.002
	SE	.023	.079	.024	.295	.768

a. Dependent Variable: BI

The analysis indicated the variance in BI was greatly explained by the standardized estimate value of the independent variables. The effects of the variables are arranged from highest to lowest in order of FC, PE, PV and SE. This indicates that FC contributed most significantly to the model, whereas SE contribution was the least.

4.1.2 Effects of Organizational Factors on BI

The research question 2 measured how organisational factors can be impacted by the intention of organisations to adopt cloud computing. Hypothesis under this research question argued that effort expectancy, hedonic motivation, and habit will positively and significantly influence organisation's behaviour and intention to adopt cloud computing technology. When testing for hypothesis H_2, Behavioural Intention (BI) was assigned the dependent variable, and the effort expectancy (EE), hedonic motivation (HM), and habit (HB) were the independent variables; a constant β_0 was initialised; the slope of regression coefficients was represented as β_1 to β_3, and ε was any other factor that might influence organisation's intention. The regression model to be tested is represented in H2. Multiple regression logit for testing hypothesis H2:

$$BI = \beta_0 + \beta_1 EE + \beta_2 HM + \beta_3 HB + \varepsilon \text{ ....} H_2$$

H_2: EE, HM, and HB have significant influence on BI of cloud computing adoption.

Multiple regression analysis was performed on the independent variables; EE, HM, and HB. This is to identify the amount of the variance that would be explained by the independent variables relating to BI. The mean and standard deviation of the descriptive statistics for the independent variables as follows: EE (N = 194; M = 3.38; SD =.54); HM (N = 194; M = 3.75; SD = .75); HB (N = 194; M = 3.41; SD = .82) and BI (N = 194; M = 3.74; SD = .74).

In order to present more truthful estimate of the dependent variable (BI) and also indicate the amount of variance in BI explained by the selected predictors, we used Pearson analysis to calculate simple correlation to identify how the predictors; EE, HM, HB correlate individually with the dependent variable, BI. The correlation existing the predictors and the dependent variable was revealed as follows: EE (r = .202, p < 0.05), HM (r = .415, p < 0.001), and HB (r = .590, p < 0.001).

According to the results, the predictors (EE, HM, and HB) explained 62.3% of the variance in BI. Table 4-6 presents the regression analysis of the model summary.

Table 4-7. Model Summary (BI) of Regression on Organizational factors.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.623[a]	.389	.379	.58086

a. Predictors: (Constant), HB, EE, HM

b. Dependent Variable: BI

The test statistic shows that the result was significant at the level p<0.001, thus, (F(3, 190) = 40.267; p < 0.001) as shown in Table 4-7. This indicates that hypothesis H2 was supported and accepted.

Table 4-8. ANOVA for Regression of BI on Organizational factors.

ANOVA[b]

Model	Sum of Squares	Df	Mean Square	F	Sig.
1 Regression	40.758	3	13.586	40.267	.000[a]
Residual	64.105	190	.337		
Total	104.863	193			

a. Predictors: (Constant), HB, EE, HM

b. Dependent Variable: BI

The regression analysis showed that HM and HB variables affect the BI of significance value (p < 0.01). However, EE was not significant as explained in Table 4-8. The standardized estimate (b) provided the following absolute values as arranged from largest to smallest: HB (b = .466, t = 8.156, p < 0.001), HM (b = .226, t =3.550, p < 0.01), and EE (b = -.88, t = -1.034, p = n.s).

Table 4-9. Coefficients for Regression Model of BI on the Organizational factors.

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Beta	Standardized Coefficients Beta	t	Sig.
1 (Constant)	1.602	.294		5.457	.000
EE	-.088	.086	-.065	-1.034	.303

HM	.226	.064	.230	3.550	.000
HB	.466	.057	.519	8.156	.000

a. Dependent Variable: BI

The analysis showed that among the variance explained in BI, HB was found to be the most contributing factor, followed by HM and finally EE as revealed by the coefficient of regression model.

4.1.3 Effects of Environmental Factors on BI

RQ3: To what extent do environmental factors influence adoption of cloud computing?

The question 3 of this research assessed influence of environmental *factors regarding adoption of cloud technology .* The hypothesis under this research question argued that social influence will positively and significantly influence *consumers behaviour and intention to adopt cloud computing technology.* When testing for hypothesis H_3, *Behavioural Intention (*BI*)* was assigned the dependent variable, and the social influence (SI) was the independent variable; β_0 was a constant; β_1 represented the slope (regression coefficient), and ε was any other factor that might influence *consumer intention*. The regression model to be tested is represented in H3. The test hypothesis:

$$BI = \beta_0 + \beta_1 SI + \varepsilon \text{ ....} H_3$$

H_3: SI has significant influence on BI of cloud computing adoption.

Moreover, we conducted a multiple regression analysis for measuring the variation of the independent variable; SI on the dependent variable; BI. The mean and standard deviation of the descriptive statistics for the predictor was revealed as: SI (N = 194; M = 3.52; SD =.74); and BI (N = 194; M = 3.74; SD = .74).

Pearson correlation analysis was performed in order to accurately determine relationship between dependent (BI) and independent variables. The selected predictor explained a major proportion of variance in the dependent variable. The test discovered that the predictor related to the dependent variable at a significance of p-values 0.000, that is SI (r = .364, p < 0.001).

Table 4-9 presents results of model summary of the multiple regression. The analysis showed that 36.33% of the variance in BI was explained by SI.

Table 4-10. Model Summary (BI) of Regression on Environmental factors.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.363[a]	.132	.127	.68853

a. Predictors: (Constant), SI

b. Dependent Variable: BI

Table 4-10 indicates the significance of test statistic: (F(1, 192) = 29.195; p < 0.001), signifying the support for hypothesis H3, therefore, would be accepted.

Table 4-11. ANOVA for Regression of BI on Organizational factors.

ANOVA[b]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.841	1	13.841	29.195	.000[a]
	Residual	91.023	192	.474		
	Total	104.863	193			

a. Predictors: (Constant), SI

b. Dependent Variable: BI

As shown in Table 4-11, the analysis of the multiple regression explains that SI variable affect BI significantly at p-value 0.000, thus (p < 0.001). The standardized estimate (b) provided an absolute value of the factor as: SI (b = .18, t = 5.403, p < 0.001).

Table 4-12. Coefficients for Regression Model of BI on the Environmental factors.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Beta	Beta		
1	(Constant)	2.378	.257		9.241	.000
	SI	.387	.072	.363	5.403	.000

a. Dependent Variable: BI

The test discovered how the coefficient of the regression model contributed significantly to SI. According to the results, it was also revealed that the predictor variable highly explained a proportional variance in BI.

4.1.4 Effects of Cloud Adoption Factors on BI

The research assessed the influence of all the cloud adoption *factors on organisations behavioural intention of cloud computing adoption.* The hypotheses under this research question argued that performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, data security, and habit will affect *organisations behavioural intention in adopting cloud technology* positively and significantly. When testing hypothesis H4, *Intention (*BI*)* was assigned the dependent variable while the predictors include PE, EE, SI, FC, HM, PV, SE, and HB; β_0 was constant; β_1 to β_8 represented the regression coefficients, while ε was other factors that were not considered in this study, which could influence *organisations intention of adopting the technology*. The regression model to be tested is represented in H4. This analysis technique is to determine which factors contribute significantly to the behavioral intention. The following logit model was specified based on the UTAUT2 framework for cloud technology adoption:

$$BI = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \beta_5 HM + \beta_6 PV + \beta_7 SE + \beta_8 HB + \varepsilon \text{ ....} H_4$$

H_4: PE, EE, SI, FC, HM, PV, SE, and HB will impact BI significantly.

As part of the analysis, we conducted multiple regression analysis to help us find the predictors variates toward BI. The following are the mean and standard deviation disclosed by the descriptive statistics for each construct: PE (N = 194; M = 4.01; SD =.78); EE (N = 194; M = 3.38; SD =.54); SI (N = 194; M = 3.52; SD =.69); FC (N = 194; M = 3.50; SD =.62); HM (N = 194; M = 3.75; SD = .75); PV (N = 194; M = 3.39; SD =.70); SE (N = 194; M = 3.79; SD =.77); HB (N = 194; M = 3.41; SD = .82) and BI (N = 194; M = 3.74; SD = .74).

We conducted Pearson analysis for determining correlations among the predictors and BI. The predictors were also used to enable us determine the proportion of variance explained by the selected predictors regarding the dependent variable (BI) in the regression models. Moreover, it helps us to accurately predict the relationship between the variables. Upon the analysis, we found out that each of the predictors correlated with the dependent variable on individual basis. The prediction values are as follows: PE (r = .534, p < 0.001), EE (r = .202, p < 0.01), SI (r = .363, p < 0.001), FC (r = .578, p < 0.001), HM (r = .415, p < 0.001), PV (r = .464, p < 0.001), SE (r = .481, p < 0.001), and HB (r = .590, p < 0.001).

According to the results of the model summary, the predictors explained up to 71.4% of BI's variations as shown by the multiple regression presented in Table 4-12.

Table 4-13. Model Summary (BI) of Regression on cloud adoption factors.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.714[a]	.509	.488	.52747

a. Predictors: (Constant), HB, PV, EE, SE, SI, FC, HM, PE

b. Dependent Variable: BI

The test statistic was significant as indicated in Table 4-13, thus: (F (8, 185**)** = 23.988; p < 0.001), therefore, hypothesis H4 was supported and accepted.

Table 4-14. ANOVA for Regression of BI on Organizational factors.

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	53.392	8	6.674	23.988	.000[a]
	Residual	51.472	185	.278		
	Total	104.863	193			

a. Predictors: (Constant), HB, PV, EE, SE, SI, FC, HM, PE

b. Dependent Variable: BI

As indicated in Table 4-14, the analysis of the multiple regression showed that FC, HB, PE, and PV variables affect the BI significantly at (p < 0.01) while SE, SI, HM, and EE were insignificant. The results of the standardized estimate (b) of the predictors values are shown from largest to smallest: FC (b = .276, t = 3.316, p < 0.01), HB (b = .262, t = 4.127, p < 0.001), PE (b = .214, t = 2.639, p < 0.01), PV (b = .208, t = 3.107, p < 0.01), SE (b = .033, t =.430, p = n.s), SI (b = -.012, t = -.172, p = n.s), HM (b = -.040, t = -.515, p = n.s), and EE (b = -.040, t = -.503, p = n.s).

Table 4-15. Coefficients for Regression Model of BI on the Organizational factors.

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Beta	Standardized Coefficients Beta	t	Sig.
1 (Constant)	.516	.319		1.618	.107
PE	.214	.081	.227	2.639	.009
EE	-.040	.080	-.030	-.503	.616
SI	-.012	.069	-.011	-.172	.864
FC	.276	.083	.230	3.319	.001
HM	-.040	.078	-.041	-.515	.607
PV	.208	.067	.199	3.107	.002
SE	.033	.078	.035	.430	.668
HB	.262	.064	.292	4.127	.000

a. Dependent Variable: BI

According to the coefficient of regression model, FC's contribution was the most while EE was the least in significance. This means, in determining the variance in organisations' behavioural intention in BI, FC explains biggest amount. The following are the arrangement of the effects of independent variables in BI from highest to lowest: FC, HB, PE, PV, SE, SI, HM, and EE.

4.1.5 Effects of Behavioural Intention (BI) on Use Behaviour (UB)

The research assessed the influence of behavioural intention *on consumers use behavioural on cloud computing adoption.* The hypothesis 5 under this research question argued that behavioural intention, facilitating condition, and habit will positively and significantly influence *consumers use behavioural to adopt cloud computing technology.* When testing for hypothesis H_5, *Use Behavioural (*UB*)* was assigned the dependent variable, then behavioural intention (BI), facilitating condition (FC), and habit (HB) were the predictors; a constant variable β_0 was introduced; the regression coefficients (slope) was represented by the variables β_1 to β_3, while an ε variable was introduced to cater for any other factor that might influence *organisations use behaviour*. The regression model to be tested is represented in H_5. The test for hypothesis in multiple regression analysis was presented as:

$$UB = \beta_0 + \beta_1\, BI + \beta_2\, FC + \beta_3\, HB + \varepsilon \text{ ....} H_5$$

H_5: BI, FC, and HB have significant influence on UB.

An analysis was undertaken to be able to determine the variation in organisation's actual use behaviour (UB) that could be explained proportionally by the predictor variables; BI, FC, and HB. The following are the mean and standard deviation derived from descriptive statistics test of the variables: BI (N = 194; M = 3.74; SD =.74); FC (N = 194; M = 3.50; SD =.62); HB (N = 194; M = 3.41; SD = .82) and UB (N = 194; M = 3.55; SD = .62).

We conducted Pearson analysis for determining the correlations among the predictors and UB. The predictors were also used to enable us determine the proportion of variance explained by the selected predictors regarding the dependent variable (BI) in the regression models. Moreover, it helps us to accurately predict the relationship between the variables. Upon the analysis, we found out that each of the predictors correlated with the dependent variable on individual basis. The results of the analysis are as follows: BI (r = .857, p < 0.001), FC (r = .806, p < 0.001), and HB (r = .841, p < 0.001). The results shows 98.2% of the variance been explained by the predictors. The regression model summary results is shown in Table 4-15.

Table 4-16. Model Summary (UB) of Regression on cloud adoption factors.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.982[a]	.965	.964	.11843

a. Predictors: (Constant), HB, BI, FC

b. Dependent Variable: UB

The significance of the test statistic was presented in Table 4-16, thus: (F (3, 190**)** = 105.890; p < 0.001), proving the support for hypothesis H5 and therefore acceptable.

Table 4-17. ANOVA for Regression of UB on behavioural intention of cloud adoption.

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71.284	3	23.761	105.890	.000[a]
	Residual	42.635	190	.224		
	Total	113.920	193			

a. Predictors: (Constant), HB, BI, FC

b. Dependent Variable: UB

According to the results, the BI, FC, and HB variables affect the UB with a significance value of ($p < 0.01$), thus, the p-value is 0.001 as disclosed in Table 4-17 based on the multiple regression analysis performed. Furthermore, in the standardized estimation (*b*), absolute values for the predictors are shown arranging from highest to lowest as follows: BI ($b = .500$, $t = 8.166$, $p < 0.001$), FC ($b = .292$, $t = 3.975$, $p < 0.001$), and HB ($b = .189$, $t = 3.339$, $p < 0.01$).

Table 4-18. Coefficients for Regression Model of UB on the behavioural intention.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Beta	Beta	t	Sig.
1	(Constant)	.005	.211		.025	.980
	BI	.500	.061	.479	8.166	.000
	FC	.292	.074	.234	3.975	.000
	HB	.189	.056	.202	3.399	.001

a. Dependent Variable: UB

According to the coefficient of regression model, BI contributed most significantly while HB contributed the least. The analysis shows that the variance explanation of the independent variables in BI is in order of: BI, FC, and HB – thus, highest to lowest.

4.2 Findings and Discussion

The empirical investigation conducted on the adopted and modified UTAUT2 model identified adoption and usage factors of cloud computing technology in a developing country – Ghana. The theoretical framework adopted for the study was supported by our data analysis. Five hypotheses were formulated where each of them proved statistically significance at level ($p<0.001$). The results of the study throws light on the relationship between key cloud adoptions variables (performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, security, and habit) against intentions of an organisation to adopt and use the technology. Our discussion focused on the TOE factors (Technological, Organizational, and Environmental) and their influence on cloud technology adoption in context of the organisation.

4.2.1 Effects of Technological Factors on BI

Four constructs were analysed under technological factors in relation to consumer behavioural intention. The coefficient of regression model revealed facilitating condition (FC) as most significant factor to the model; follow by performance expectancy (PE), then, price value (PV). Security (SE) on the other hand, has no significance at all. The analysis indicates that in Ghana, the availability of the required facility (thus, resources, knowledge, system compatibility, and enough internet experience) to support cloud computing evolvement is assured. Also, the relative advantages of cloud technology such as usefulness, quick task accomplishment, performance improvement, efficiency and effectiveness, use of latest technology, provision of reliable and accurate information is well understood. Perhaps, they do not trust the security of the platform in regard to their sensitive data.

4.2.2 Effects of Organizational Factors on BI

Regression analysis on organizational factors discovered habit (HB) as the highest predicative value, next to it is hedonic motivation (HM), and finally, effort expectancy (EE). Presumably, this could mean that it would have been easy for the consumers to use the cloud service regularly because of its educative and entertaining measures, which enable them overcome difficult challenges. On the contrary, they may need little training, trial versions, or perhaps, there are complexity deters them.

4.2.3 Effects of Environmental Factors on BI

The analysis performed on environmental factors discovered that social influence (SI) positively and significantly influence organisations' behavioural intention of adopting cloud computing technology. Obviously, people may preferably want to have access to products and service at the comfort of their location without necessarily traveling to the business centres; this enhances time and cost saving, which, at the long round increases productivity – cloud technology would be the best option.

4.2.4 Effects of Cloud Adoption Factors (TOE) on BI

Regression analysis conducted on the eight constructs (PE, EE, SI, FC, HM, PV, SE, and HB) revealed four constructs (FC, HB, PE, and PV) influencing the dependent variable (BI) positively and significantly, with facilitating condition (FC) explaining the greatest amount of variance in BI. Nonetheless, effort expectancy (EE), hedonic motivation (HM), and social influence (SI) rather influence BI negatively, whereas, security (SE) was insignificant. Surprisingly, regression analysis conducted on environmental factors proved SI to be positively significant, but however, turned negative when among the eight construct.

Apparently, this may be due to the lack of trust (data security). The organisations do not trust cloud services for the protection and privacy of their sensitive data, hence, do not bother about the social influence.

4.2.5 Effects of Behavioural Intention (BI) on Use Behaviour (UB)

According to the analysis performed on user behaviour, the coefficient of regression model showed that BI contributed most significantly to the model followed by facilitating condition (FC), whereas HB contributed the least. This could probably mean the organisations have the intention, resources, and desire to use the cloud service once other factors such as trust, data security, and data protection measures are put in place.

In cloud technology adoption, the three main factors that are considered as essential predictors are the technological, organizational, and environmental (TOE).

After investigating effects on intention of using and actual use behaviour towards cloud technology usage by organisations on the TOE factors, our results indicated that four of the constructs (facilitating condition, performance expectancy, price value, and habit) exerted significant but varying effects on behavioural intention. Among the four constructs, facilitating condition exerted the greatest effect on ownership. The next factor that contributed intensively is habit. Performance expectancy and price value however contributed less. On the other hand, the effect of effort expectancy, social influence, hedonic motivation, as well as security was found insignificant. Moreover, the examination of the direct effect of Actual Use shows Facilitating Condition and Behavioural Intention having great significant effects, while the effect of habit on actual use was minimal.

Previous studies on cloud adoption literature highlighted the effects of technological, organizational, and environmental factors on intention of using and actual use behaviour toward cloud computing. Several previous studies have highlighted the role of facilitating conditions (Yang & Forney, 2013; Akbar, 2013), habit (Akbar, 2013), performance expectancy (Bhatiasevi, 2015; Hashim & Hassan, 2015; Dhulla & Mathur, 2014; Akbar, 2013; Venkatesh et al., 2012), and price value (Dhulla & Mathur, 2014; Venkatesh et al., 2012) on intentions of adopting and using cloud computing technology. The outcome of our study is consistent with these earlier studies. This could probably mean that these factors are not influenced by cultural or national differences.

However, our results did not discover effect of effort expectancy, hedonic motivation, social influence, and security to be significant in the Ghanaian context as found by other cloud computing studies (Bhatiasevi, 2015; Hashim & Hassan, 2015; Dhulla & Mathur, 2014; Yang & Forney, 2013; Venkatesh et al., 2012). In addition, perceived effort expectancy, lack of social influence, lack of motivation, and inadequate security serve as barriers to cloud computing in the Ghanaian context. After analysing security with other constructs, there was a drastic change in the behaviour of hedonic motivation by having a negative influence. Seemingly, once trust for security is lacked, consumers would not be motivated in making any effort to even try, which, leaded to the fall of effort expectancy.

This could probably be due to the high rate of cybercrime activities in the country (Joy News, July 31, 2013; Ghana Business News, December 2, 2010). Obviously, organisations may not want to be victims of cybercrime activities, therefore, may not even want to be influenced by social environment in adopting the cloud technology no matter its advantageous benefits.

5. RECOMMENDATION

For an effective adoption of the cloud services, this study recommends extensive awareness campaigns to targeted potential cloud computing users in regard to cloud data privacy. Individuals should be made known the security policies and measures in place. Furthermore, individuals should be educated on how they could be security conscious in order to protect their sensitive information against cyber theft. Cloud users should always be mindful of the information they provide online, the device they use, and the web sites they visit in order to prevent their information from reaching cybercriminals.

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