UNIVERSITY OF NAIROBI

SCHOOL OF COMPUTING AND INFORMATICS

POST ADOPTION EVALUATION MODEL FOR CLOUD COMPUTING SERVICES UTILIZATION IN UNIVERSITIES IN KENYA

BY

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A Research Thesis submitted in partial fulfillment for the requirement of Master of Science in Information Systems Degree of the University of Nairobi

Declaration

I, **Muhambe Titus Mukisa** declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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APPROVAL

This research project has been submitted as part of fulfillment of requirements for the Master of Science in Information Systems with my approval as the Supervisor:

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Abstract

Cloud computing is a new computing paradigm that is gaining popularity in Kenya and the world over and as such this study was conducted in order to gain a better understanding of this phenomenon. This study was primarily aimed at; identifying the primary factors that influence the acceptance and use of cloud computing services in Universities in Kenya, establishing the moderating factors to the identified primary factors, present a model for post adoption evaluation of cloud computing services utilization in universities in Kenya and compare utilization levels of the different categories of cloud computing services among university students in Kenya. We reviewed literature on technology adoption theories and models, focusing on the postulates of these theories and models, their strengths and weaknesses, selected case studies where each of the theories or model had been used in technology adoption studies, the results obtained and the conclusions drawn. Our research methodology involved the use of questionnaires and Focus Group Discussion (FGD) to gather data, analysis of the quantitative data was through computation of partial correlation coefficients between the dependent and independent variables and using the Focus Group Discussion to explain some of the observed trends and phenomenon. Our findings revealed that Performance Expectancy and Facilitating Conditions were the two main factors that influence Behavioral Intention to accept cloud computing services, while behavioral intention directly influences use behavior. Effort Expectancy and Social Influence constructs were both found have no significant influence on behavioral intention. The correlation between Performance Expectancy and Behavioral Intention was moderated by gender and age, while that between Facilitating Condition and Behavioral Intention was moderated by gender, age and duration of use. Facilitating condition was found to directly affect behavioral intention contrary to the findings of Venkatesh et al., (2003), which established that facilitating conditions directly influences use behavior. The Focus Group Discussion results revealed that personal ego negatively influenced the willingness of individuals to admit that they were influenced by others towards adoption and use cloud computing services. Based on these findings, a model for post adoption evaluation of cloud computing services is presented. Due to financial constraint, the study did not introduce cloud computing services to the students in order to learn the adopter’s behavior before, during and after adoption of the cloud computing services. The resulting model was derived from the data obtained from the students who were

already using cloud services. It is therefore recommended that future research work on cloud services adoption and use should include observation of the cloud services adoption process and behavior change of the students before, during and after adoption. This would allow for the validation of the resulting model presented here.

Secondly, random sampling did not allow us to collect fair and balanced samples as relates to factors such as age, gender and duration of use, which may have profound moderation effects on the model relationships. It is therefore recommended that future research should adopt or use purposeful sampling in order to gain proper representation of students in terms of age, gender and duration of use.

Dedication

To Almighty Jehovah God and to my Lord and Savior Jesus Christ

My Wife Linda Mkoya (HB)

My precious Parents; Evans Mukisa Peru and Joyce Kageha Mukisa

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I am grateful to Jehovah God for the strength and capacity that enabled me to finish this work. I am forever grateful to my friends, fellow students, colleagues at the Institute of Advanced Technology and University of Nairobi; School of Computing and Informatics supervising and examining panel who were all key to the success of the research process.

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- Pastoral team at Cornerstone Faith Assembly fellowship led by Bishop Dr. Francis M. Kamau and Pastor Amos Mwangi; I am forever grateful for your prayers.

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List of Abbreviations

CUEA – Catholic University of East Africa

EE - Effort Expectancy

FC – Facilitating Condition

IaaS - Infrastructure as a Service

TUK – The Technical University of Kenya

PaaS - Platform as a Service

PE – Performance Expectancy

SaaS – Software as a Service

SI – Social Influence

TAM – Technology Acceptance Model

TPB – Theory of Planned Behavior

TRA – Theory of Reasoned Action

UTAUT – Unified Theory of Acceptance and Use of Technology

UoN – University of Nairobi

$\mathbf{R^2}$ – Variance

RAM – Random Access Memory

CPU – Central Processing Unit

Key Terminologies

Computing

Describes any activities of using and/or developing computing devices; hardware and software

Cloud

Abstraction of the setup and configuration details of the “internet” and represented in computer network schematic diagrams using a “cloud” symbol (Sultan, 2010).

Cloud Computing

A paradigm that allows on demand access to a pool of metered computing resources that include applications, platform and hardware infrastructure, offered as a service by a provider/vendor via the internet infrastructure

Model

A hypothetical structure that is used in the investigation of interrelations between the elements

Theory

A supposition or a system of ideas intended to explain something, especially one based on general principles independent of the thing to be explained

Technology adoption/Acceptance

The first use or acceptance of the new technology or new product

Population

All items in any field of inquiry or the entire mass of observations, which is the parent group from which a sample is to be formed

CHAPTER 1: INTRODUCTION

1.1 Background: Cloud Computing

Computers have become an indispensable part of the daily life. We find them being applied in almost all fields; from business, medical filed, engineering field, agriculture, space exploration and academics. The adoption and use of computers and computing technology is aimed at saving costs, reducing amounts of time required to accomplish complex computational tasks, ensuring accuracy in computations, increasing production speeds and precision and automating highly repetitive tasks. There has been a steady increase in the need for computing and computing services in the various fields. For any user; whether individuals, small or large corporate firms, several challenges are presented and these include; acquiring and owning of the resources required to meet and satisfy their computing needs and in addition, where the situations demand there may be need to lay a complex data communication network infrastructure, carry out routine maintenance, periodic upgrades of hardware components, setting up, configuring and periodic upgrades to the system and application software components.

Cloud Computing, a recent technology development presents a paradigm shift in computing (Luis et al., 2008). The shift represents a move away from personal computers and enterprise server systems (e.g. application servers and file servers) to a “cloud” of computers. Applications and resources are accessed from the cloud as opposed to the traditional environment where they are accessed either from the main frame computers using dump terminals or from dedicated server systems housed in the premises of the organization or from standalone intelligent terminals with processing capabilities like personal computers or laptops. Some scholars have argued that even though the cloud computing term is new, the concept is not new (Shimba, 2010; Weinhardt et al., 2009) because it borrows from other computing paradigms such as utility computing and grid computing (Luis et al., 2008, Wang and Laszewski, 2008, Buyya et al., 2008). Zhang et al., (2010) strongly echoes this argument by stating that there is actually nothing new about the notion of cloud computing, given the fact that it includes existing technologies such as Centralized and Distributed Computing, Utility Computing, and Virtualization.

According to Aderemi, and Oluwaseyi (2011), cloud computing came into the foreground as a result of advances in virtualization, distributed computing with server clusters and an increase in the availability of broadband internet access. Based on this, cloud computing can be viewed as the convergence of the three major arms of technology: virtualization, where applications are separated from infrastructure; utility computing and packaging of computer resources in the form of metered services that are accessible via the internet infrastructure (Aderemi and Oluwaseyi, 2011). Weinhardt et al (2009), offers a different perspective by placing cloud computing in technology timeline and arguing that cloud computing represents fifth generation of computing technology; after mainframe computing, personal computing, client-server computing and the web.

1.2 Problem Definition

User acceptance or rejection of a new technology has for a long time been cited as the greatest aid or hindrance to success of any new technology (Gould, Boies & Lewis, 1991; McCarroll, 1991). Numerous technology adoption studies focusing on establishing factors that influence *behavioral intention* and *use behavior* of various technologies have been carried out mainly in United States, Europe, Australia, China, Japan, Singapore and Malaysia. Studies on adoption and use of cloud computing services have been carried out in the same regions but it is worth noting that these regions of the world have a highly developed internet infrastructure, high levels of internet permeation and high utilization levels of internet and associated services. A significant number of these studies have contributed immensely to the success of these technologies by enabling stakeholders to understand and take advantage of the factors that influence "behavioral intention" and the "use behavior". In Kenya, the recent development as regards cloud computing services provision has witnessed the introduction of "Safari Cloud" by the telecommunication company, Safaricom Limited and this serves as evidence of a growing interest in this technology by local investors. The success in the adoption and use of cloud computing technology in Kenya will depend on the ability of the *movers* of this technology; researchers and vendors/providers to identify and take advantage of the factors that influence Behavioral intention and the Use Behavior. The research focused on the need to establish factors that influence behavioral intention and the use behavior of the cloud computing services within Kenyan Universities.

1.3 Research objectives

I. Establish and compare the levels of utilization of Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS) in the Universities in Kenya

II. Establish factors that influence the acceptance and use of cloud computing services in universities in Kenya.

III. Determine the moderators to the factors that influence acceptance and use of cloud computing services in universities in Kenya.

IV. Present a model for post adoption evaluation of cloud computing services utilization in universities in Kenya

1.4 Research Questions

I. Which category of computing service; PaaS, SaaS and IaaS is most utilized in the universities in Kenya?

II. What factors influence the acceptance and usage of cloud computing services in universities in Kenya?

III. What is the moderating effect of age, gender and duration on the factors that influence acceptance and use of cloud computing services in Kenyan Universities?

IV. What is the appropriate model for post adoption evaluation of cloud computing services in universities in Kenya?

1.5 Justification of the study

The findings of the study will be important to three categories of people; the academic researchers, Cloud Computing services providers and institutions of higher learning.

- Academically, it has added to the body of knowledge and contributed positively towards understanding cloud computing adoption among individual users in the universities in Kenya; by establishing the factors that influence the acceptance and usage of cloud computing services and how moderating factors affect the relationship between the primary determinants and Behavioral Intention to accept and use cloud services.

- The benefit will also extend to cloud services vendors/provides. By understanding factors that influence individual's Behavioral Intention and Use Behavior in cloud computing service adoption, they can take advantage of the information in this study report to tailor products and services to address user needs in addition to achieving focused marketing of the same.

- Finally, the report will also be useful to the institutions that may have plans of rolling out a cloud computing infrastructure. By understanding the university student's behavioral intention towards adoption of cloud computing, the institutions can design their cloud infrastructures and cloud services with input from this report.

1.6 Scope of the Research

The research was limited to evaluation of student's use of publicly available cloud computing services. It covered four universities in Kenya; two public universities - University of Nairobi (UoN), The Technical University of Kenya (TUK) located in Nairobi and two private universities – Strathmore University and Catholic University of East Africa (CUEA) located in Nairobi as well. Further, study was also be limited to studying the usage of Email, Google Docs, YouTube, Sendspace, Dropbox, Sky Drive, Google Apps Engine, Ubuntu-one and Windows Azure) and not the functional specifications, configuration setups or deployment models behind Cloud Computing.

1.7 Chapter Summary

The remainder of this report is organized as follows;

Chapter 2 Focuses on reviewing literature related to principles of cloud computing, technology adoption and technology adoption models and frameworks

Chapter 3 covers research methodology: research design, population size and sample, conceptual model, hypothesis formulation, data collection instrument and data analysis approach

Chapter 4 Presents the results; general characteristics of the student, Pearson correlation statistics and cross tabulation between constructs, moderating factors and a detailed discussion of these results

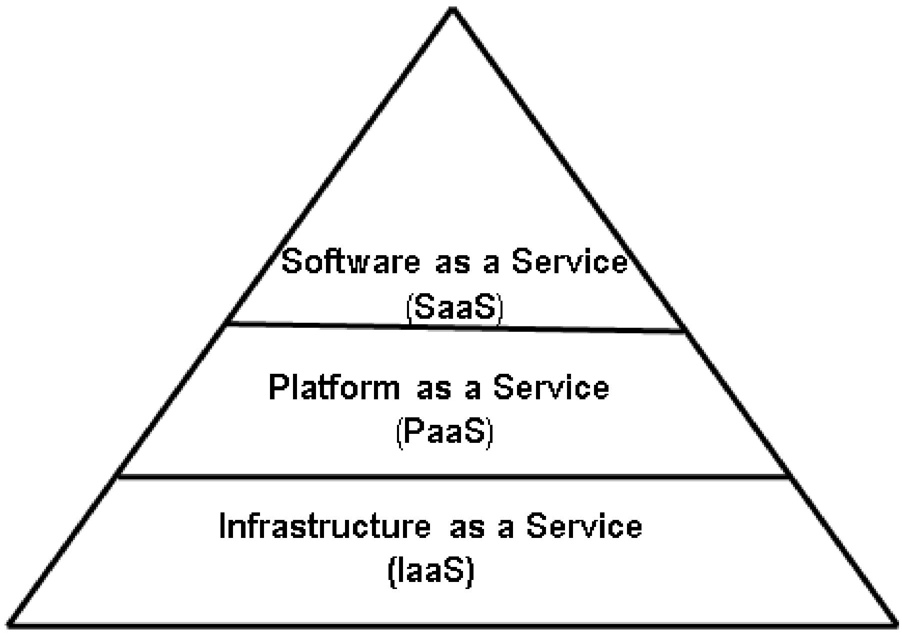
Chapter 5 presents the conclusion of the study, research contributions, research evaluation and assessment and recommendations for further work

CHAPTER 2: LITERATURE REVIEW

2.1 The cloud service Models

In cloud computing, all available resources; infrastructure, platform and applications, are delivered in the form of services (Aderemi and Oluwaseyi, 2011). The Cloud computing technology can be visualized and described using the XaaS taxonomy that was developed and first used by Scott Maxwell in 2006 (Ranjan, 2012). The "X" can be substituted with Software, Platform or Infrastructure, while the "S" represents Service. Zhang and Chen (2010) organized the different types of services available in the cloud, into a layered architecture. The layered architecture attempts to show the dependency and relationship between the layers in the cloud infrastructure i.e. the layer above depends on the one beneath it. The service models can take any of the three formats; Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS), as shown in Figure 1.0.

Figure 1.0: *Layered Cloud services diagrams*



Source: *Aderemi and Oluwaseyi, 2011*

2.1.1 Software as a Service (*SaaS*)

The Software as a Service (SaaS) forms the top layer of the layered cloud architecture (*Figure 1.0 above*) where applications hosted on the provider's network are run and interacted with via a web browser, which is a thin client interface that is normally hosted on a remote client. The software applications are made available to multiple end users via the internet infrastructure. The users do not have control or access to the underlying cloud infrastructure that hosts the software application. Current and most popular examples of SaaS service model include Google Docs, YouTube and Gmail from Google (Chappell, 2009) and Salesforce's Customer Relationship Management software (Varia, 2009).

2.1.2 Platform as a Service (PaaS)

The middle layer of the layered cloud architecture (*Figure 1.0 above*) forms the platform, which is an environment on the provider/vendors cloud infrastructure designed to enable developers create/develop, test and even deploy applications on the vendor's or provider's platform (Allan, 2010; Bret and George, 2010). The provider/vendor has the responsibility of ensuring that the cloud infrastructure environment has the required platform, flexibility and the necessary development tools that may include a set of programming languages. Just like in SaaS service model, PaaS users do not have access or control of the underlying structure. Among the most popular examples of this service model currently include Google App Engine (Rayport and Heyward, 2009) and Microsoft Azure (Pastaki et al, 2009).

2.1.3 Infrastructure as a Service (IaaS)

The Infrastructure as a service layer at the base of the layered architecture (*Figure 1.0*) is a virtualized environment that makes it possible to split a single physical piece of hardware into independent, self-governed environments, which can be scaled in terms of CPU, RAM and Disk (Victorde, 2010). In this service model, users acquire computing resources that may include processing power, memory and storage from an IaaS provider. The acquired resources can then be used to deploy and run the users applications and data storage (Mel, 2010). This service model permits users to access the underlying infrastructure in order to configure virtual machines. The virtualization technology provides a virtual and elastic infrastructure environment on the vendor/provider cloud infrastructure that allows access and configuration of hardware into complete and independent, self-governed environments that consist of CPU, memory, disk; for storage and operating system (Sun Microsystems, 2009). Common examples of IaaS service models include Sendspace.com services, Amazon Web Services, EC2 and S3 (Khajeh-Hosseini, 2010).

2.2 The Deployment Models

This section describes the various cloud deployment models which include public cloud, private cloud, community cloud and hybrid cloud.

2.2.1 Public Cloud

Public cloud is the traditional and most common way of providing cloud services, where a vendor or company provides various cloud services namely SaaS, IaaS and PaaS via the internet infrastructure. Each potential customer can gain access to their favorite cloud services by making a formal application online and going through the registration procedure required by the cloud services provider. In this deployment model, the services are visible to all the internet users and accessible to multiple users at the same time but may not necessarily be for free. The public cloud infrastructure traverses national and regional geographical boundaries. The management and control is the responsibility of the company that provides or sells the services (Armbrust et al., 2010; IBM, 2010; Victor et al., 2010). Examples of publicly available cloud services include; Safari Cloud, from Safaricom Limited here in Kenya, Google AppEngine from Google, Amazon Elastic Compute Cloud (EC2), IBM's Blue Cloud, and Windows Azure Services Platform. The public cloud services present several advantages to the user in the sense that the user only pays for what they use, it can easily scale to meet the needs of the user, the application, hardware and related maintenance costs are met by the cloud provider.

2.2.2 Private Cloud

Private cloud or internal cloud or corporate cloud describes a proprietary cloud architecture that provides hosted services to a limited number of people. It is separated from the internet or public networks by a firewall and is primarily accessed by employees of the particular organization. It is built, managed, and directly controlled by a single organization that owns the cloud infrastructure (Armbrust et al., 2010; IBM, 2010; Victor *et al*., 2010). There are several advantages of implementing private cloud and these include; infrastructure and applications that are tailored to the needs of the organization, the security design and implementation is done by the organization, which gives a sense control and finally, it also saves on the cost of implementing network and data communication infrastructures for organizations that have multiple braches spread across the globe. An example of private cloud is the one implemented by the United Kingdom based law firm, Taylor Vinters, which has its headquarters in Cambridge and other offices in London and Singapore

2.2.3 Community Cloud

In this deployment model, the cloud infrastructure is shared by several organizations (Dillon et al, 2010), that together form the community. The management of the infrastructure may be shared between the organization through provision of a common management policy, while in some cases the management and control may be done by a third party on behalf of the organizations that form the community (Thomas, 2009). An example of the community cloud is Federal Community Cloud (IBM, 2010), implemented for the federal government of the United States by IBM. The community cloud presented the advantage of cost sharing between the entities that come together to establish the cloud and ensures access to the same information for participating entities, making collaboration easier.

2.2.4 Hybrid Cloud

Hybrid model is a cloud infrastructure that incorporates both public and private clouds (Babcock, 2010). It is mostly adopted where an organization builds a private cloud for the most sensitive and essential services and then outsources cloud services for the less-essential services from a public cloud service provider (Dustin and Scott, 2009; Victor *et al.,* 2010).
It enables organizations to balance between making services that core to its operations and the cost associated with it. Therefore the implementation of hybrid cloud plays a major role in the reduction of capital expenses on the organization's information technology infrastructure implementation, because a portion of the services required by the organization are outsourced from public cloud providers. An example is the Cross Country TravelCorps private cloud.

2.3 Technology Adoption

The world has witnessed technology explosion in the field of computing and information technology and these developments have spurred research interested in predicting and explaining the adoption and use technology (Venkatesh et al, 2003). Reviews of literature on technology adoption show that research concerning technology adoption has been done for close to three decades (Agarwal & Prasad, 1999; Davis, 1986; Venkatesh & Davis, 2000; Ochieng, 2012; Taylor, 2011; Venkatesh et al., 2003; Wang and Shih, 2009). Most of this research has been carried out in the United States of America, Europe, Australia and Japan and china, but gradually the research on technology adoption is gaining momentum in Africa and the rest of the developing world (Ochieng, 2012).

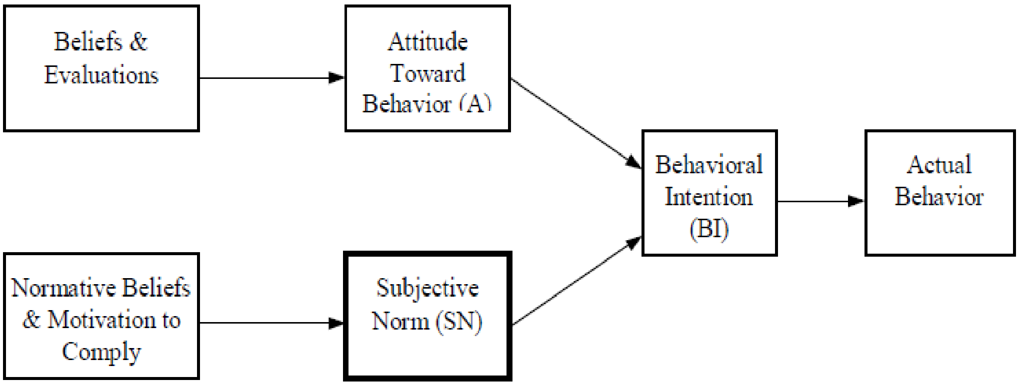
The human factors present the most complex and challenging elements In technology adoption studies, and thus has led to increased research activities. Among the research activities that are of interest to researchers include establishing the factors that influence the Behavioral Intention and Use Behavior (Al-Adawi et al., 2005). A number of theories and models have been developed for the purpose of evaluating and explaining technology adoption by individual users. Research findings from various adoption studies focusing on acceptance/adoption and usage of different technologies have shown variations in factors that influence adoption and levels of technology acceptance, depending on the model or theory applied in the research and the region of the world where the research was carried out.

The most cited models and theories include; Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM) and its extended version called TAM 2, Social-Cognitive Theory (SCT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Each of the models or theory has its own defined independent and dependent variables. Some variables have been found to overlap across models (Morris and Dhillon, 1996), even though they may assume different names under the respective models. The existence of various technology adoption models and theories has given birth to a lot of debates on the suitability of some of the models in explaining technology acceptance and adoption.

2.3.1 Theory of Reasoned Action

The Theory of Reasoned Action (Ajzen et al., 1980; Fishbein and Ajzen, 1975) was among the first technology adoption theories to be developed. It is a well-established and accepted model that has been applied to explain behavior across a variety of research settings and environments (Vankatesh, 1999; Chau, 1996). According to Fishbein and Ajzen (1975), TRA predicts the behavior of a given individual through their behavioral intentions, which in turn is determined by the person's attitudes and subjective norm (social influence) as shown Figure 2 below.

Figure 2: *Theory of Reasoned Action*



Source*: Theory of Reasoned Action (TRA): Fishbein & Ajzen (1975)*

Behavioral Intention is defined as the strength of a person's intention to adopt a certain behavior (Davis et al., 1989). *Attitude Towards Behavior* refers to the negative or positive way the individual evaluates the performance effect of a given behavior (Fishbein & Ajzen, 1975). *Subjective norm* is defined as beliefs about what others think about the behavior (Fishbein and Ajzen, 1975). When an individual believes that those who are important or significant to him/her perceives or views the outcome of performing the behavior as positive, they are more likely perform the behavior.

The two constructs in this theory makes it important in technology adoption because it approaches the subject of adoption using two dimensions (Chau et al., 2010). First, the social psychological dimension where behavioral choice is envisioned as a psychological process in which beliefs influence attitudes towards behavioral intention, which may result into adoption or rejection of a technology and secondly, the external factors dimension which forms the subjective norm. Under subjective norm, the role of social influence on behavioral intentions is considered. The model is important in technology adoption studies because it takes into consideration both the internal and external factors that may play a role in determining behavioral intention of an individual towards the adoption or rejection of a technology.

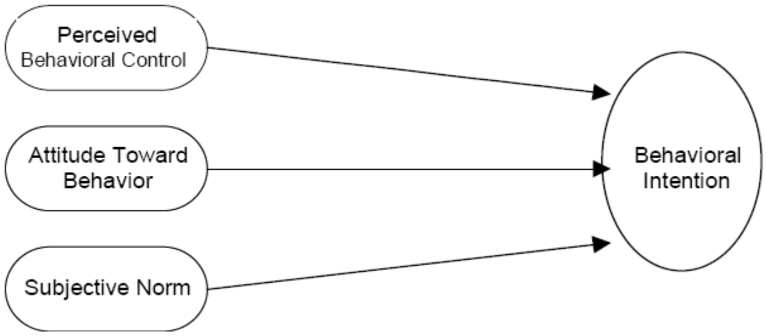
Ajzen (1991) points out that the main shortcoming of TRA is the assumption that individual behavior is controlled volitionally, which may not always the case. Ajzen (1991) argues that some individuals have little control of their behavior and in some cases some individual think they have little control of their own behavior. The theory does not consider the effect of prevailing conditions and the influence that this may have on the Behavioral Intention.

The subjective norm, otherwise called the social influence from this model was used in the conceptual for this research. This was because there was a need to establish the effect or role played by social influence towards the acceptance and use of cloud services among students in Kenyan Universities. The review of this model also pointed us to the need to incorporate in the final conceptual model, elements that would explain the effect of the prevailing condition on technology adoption.

2.3.2 Theory of Planned Behavior (TPB)

In an attempt to address the short coming of TRA, Theory of Planned Behavior (TPB) incorporates the "Perceived Behavior Control" construct. The construct is introduced to primarily account for scenarios where the control over the target behavior is not entirely volitional (Ajzen, 1985). TPB presents three constructs that influence behavioral intention; Perceived Behavioral Control, Attitude Toward a Behavior and Subjective Norm (*Figure 3 below*). Perceived behavior control is described as the perception of the ease or difficulty of performing the behavior (Ajzen, 1991).

Figure 3: *Theory of Planned Behavior*



Source: *Theory of Planned Behavior (Ajzen, 1985)*

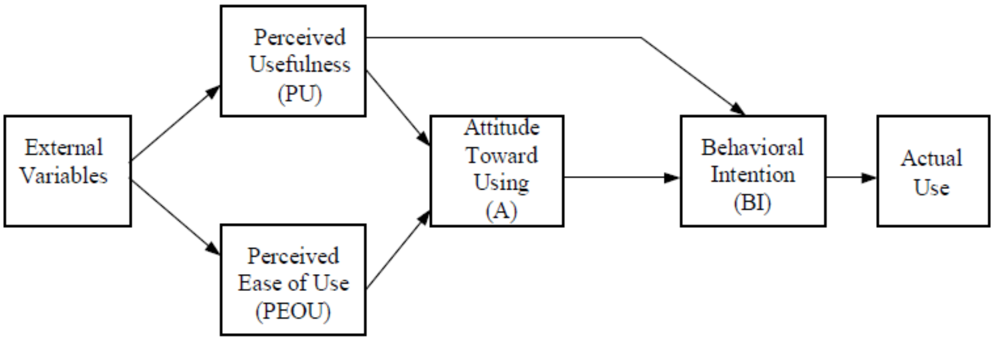
"Attitude Toward Behavior" refers to the negative or positive way the individual evaluates the performance effect of a given behavior. The Subjective Norm is an individual's perception of how others will view their performance of the given behavior. A significant number of studies have shown that TPB is applicable to various domains and provides a valuable framework for explaining and predicting the acceptance of a new technology (Hung et al, 2006). Scholars have further argued in support of TPB by saying that its constructs are easy to *operationalize* (Limayem, Khalifa and Frini 2000). Taylor (2011), while studying students use of cloud computing applications (Google Docs) at Appalachian State University in the state of North Caroline in the United States of America, used the Theory of Planned Behavior and established that perceived behavioral control, subjective norm, behavioral attitude were direct determinants of behavioral intention, which in turn directly influenced the use behavior.

However, TPB has been criticized for failing to account for effect on adoption of factors like perceived levels of complexity to the user of a given technology, the role of experience and voluntariness and perceived usefulness of a technology. We reviewed this model with the aim of establishing its strengths, weaknesses and shortcomings, as established by other scholars through their research. This led us to include perceived usefulness also known as performance expectancy as an independent variable in the conceptual model. We sought to establish the role played the perception a user may have about the usefulness of a cloud service before accepting and using the service. Furthermore, because of the criticism leveled against this theory, it made us to consider the need to establish the effect of perceived levels of complexity, otherwise called *effort expectancy* to the user of the technology to be adopted.

2.3.3 Technology Acceptance Model (TAM) and TAM 2

Technology Acceptance Model (TAM) developed by Davis (1989) and currently one of the most popular model, was developed to specifically deal with the prediction of the acceptability of an information system. The model suggests that the acceptability of an information system is primarily determined by two beliefs: Perceived Usefulness and Perceived Ease of use. Theoretically, TAM finds its grounding in Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA) which states that beliefs influence attitudes, which lead to intentions and finally use behavior and hence can be used to explain an individual's behavior when adopting a new technology. TAM highlights the influence derived from external variables and internal belief and indicates that an information system adoption and use can be explained on the basis of the perceived ease of the use and perceived usefulness (Davis, 1989). Perceived usefulness is defined as the degree to which a person believes that the use of a system will improve his/her performance. Perceived ease of use on the other hand refers to the degree to which a person believes that the use of a system will be effortless. It measures the effort that the user has to exert to use the system.

Figure 4: *Technology Adoption Model (TAM)*



***Source**: Technology Acceptance Model (TAM) (Based on Davis et al. 1989)*

The TAM model has been used extensively to study technology acceptance. Huang et al. (2007) employed TAM to examine the acceptance of mobile learning, while Liaw (2008) investigated students' perceived satisfaction, behavioral intention, and effectiveness of e-learning.

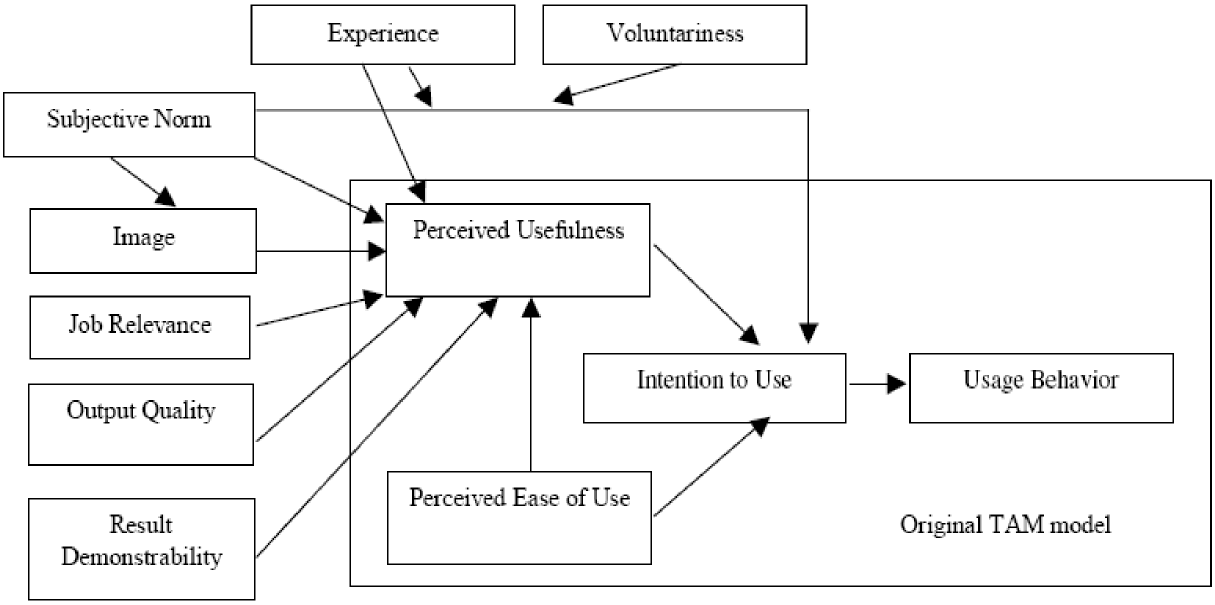
TAM has received wide support from numerous scholars through validations and confirmatory studies for its ability to predict the behavioral intention and actual use of information systems (Davis, 1989; Davis et al., 1989; Lu et al., 2003). Davis et al (1989) and Robey (1996) have argued in support of TAM by stating that it has contributed greatly towards understanding information system acceptance and use behaviors due to the fact it more specific to information systems.

However, since the model in its original design emphasizes on the design characteristics of system, scholars have pointed out that it does not account for social influence, an extremely important factor in the adoption and utilization of new information systems (Davis, 1989; and Davis et al., 1989; Fu et al., 2006; Mathieson, K., 1991). Furthermore, it was found that TAM excludes some important sources of variance and does not consider challenges such as time or money constraints as factors that would prevent an individual from using information system. According to Mathieson et al (2001), TAM has failed to provide meaningful information about the user acceptance of a particular technology due to its generality. Straub et al (1997) point out that there is a struggle among researchers to understand whether or not TAM is applicable in all cultural contexts since it has majorly been validated in United States and Europe. In a research conducted in United States, Switzerland and Japan focusing on adoption of emails at three different airlines, it produced evidence that suggested that culture could be a factor. In the study, the results from US and Switzerland were to a great extend consistent with one another and hence validated TAM while the results from Japan could not validate TAM. This led to speculation that it might have been due to cultural differences. TAM does not account for cultural or social variables. Davis (1989:334), a pioneer scholar of TAM admitted that his model needed further research in order to shed more light on the generality of its findings. Other scholars have argued that since TAM is primarily designed to be a predictive tool whose underlying assumption is that beliefs concerning usefulness and ease of use are always the principal determinants of any use decision, it fails in cases where there is need to establish motives for specific observed behavior (Mathieson, 1991). According to Venkatesh (2000), TAM is powerful in helping to predict acceptance, but it does explain acceptance in ways that guide development beyond suggesting that system characteristics impact usefulness and ease of use, thereby placing limitation on the ability to meaningfully design interferences to promote acceptance.

Consequently, a modified TAM model, referred to as extended Technology Acceptance Model or TAM 2 was proposed for contemporary technologies studies (Chau and Hu, 2001).

TAM 2, just like TAM posits that an individual's intention to use a system is determined by two beliefs: perceived usefulness and perceived ease of use. TAM 2 attempts to give a better understanding of the determinants of perceived usefulness by incorporating two additional theoretical constructs: cognitive instrumental processes and social influence processes. The four cognitive factors that influence perceived usefulness are: job relevance, output quality, result demonstrability and perceived ease of use. The three social forces that influence perceived usefulness are: subjective norm, image and voluntariness (Venkatesh and Davis, 2000).

Figure 5: *Technology Adoption Model 2*



Source*: Technology Acceptance Model 2 (TAM 2) Source Venkatesh, V. and Davis, F.D (2000)*

Subjective norm is defined as an individual's perception about what the people who are important to him/her think of him/her should or should not use the technology. Image is the degree to which one perceives the use of the technology as a means of enhancing one's status within a social group. Voluntariness is the extent to which one perceives the adoption decision as non-mandatory. Job relevance is an individual's perception of the degree to which the technology is applicable to his or her job. Output quality is an individual's perception of how well a system performs tasks necessary to his or her job. Result demonstrability is the tangibility of the results when using the technology. Venkatesh and Davis (2000) argue that without any positive demonstrable results from a given technology, the implementation of an effective system can lead to failure if the perceived usefulness cannot be demonstrated. This model is significant improvement from the previously mentioned models and important to technology adoption studies because it introduces and accounts for the effect of making technology adoption mandatory or voluntary. It also accounts for the effect of experience on both the subjective norm and perceived usefulness.

The inclusion of the effort expectancy in our research conceptual model was informed by the fact that it had been included in TAM and TAM-2 as perceived ease of use and numerous technology adoption research findings had established that this factor significantly influenced adoption and use of new technology. We therefore need to establish what role if any, was played by this factor in cloud computing adoption among students in Kenyan Universities. TAM-2 includes experience as a moderator to the perceived usefulness factor. This influenced the inclusion of moderator factor *duration of use* in our research conceptual model, in order to establish how duration of use influenced adoption and use of cloud services among students in Kenyan universities. Further, because of the criticism by scholars that both TAM and TAM2 do not explain the effect of facilitating condition for example availability of resources required to enable the use to adopt and use a technology, we sought to establish the effect of facilitating conditions in cloud services adoption.

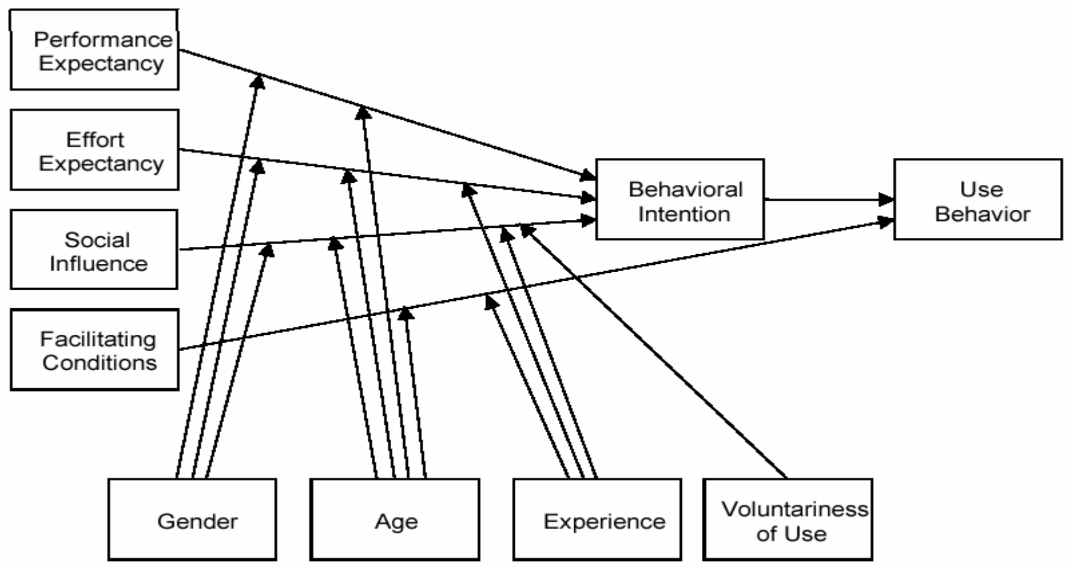
2.3.4 Unified Theory of Acceptance and Use of Technology

To confront and address some the limitations and uncertainties that multiple models may pose to the researcher, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was developed. The model was designed with the aim of simplifying the understanding of Behavioral Intention and Use Behavior as the dependent variables (Venkatesh et al., 2003) and achieving of a unified view of user acceptance of technology (Abdulwahab and Dahalin, 2010; Venkatesh et al., 2003). UTAUT model was developed through consolidating of previous technology acceptance theories and models (Venkatesh et al, 2003). It combines eight previous adoption theories through empirical studies. The models include; the Theory of Reasoned Action (Davis et al. 1989, Technology Acceptance Model (Davis, 1989), the Motivational Model (Davis et al., 1992), The Theory of Planned Behavior (Ajzen, 1991), a model combining the technology acceptance model and the Theory of

Planned Behaviour (Taylor and Todd 1995), the model of PC utilization (Thompson et al., 1991), the Innovation Diffusion Theory (Rogers, 1995), and Social Cognitive Theory (Compeau and Higgins, 1995).

The theory holds that four key constructs; Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions are direct determinants of Behavioral Intention and Use Behavior (Venkatesh et al., 2003). Gender, Age, Experience and Voluntariness of use are posited to mediate the impact of the four primary constructs on behavioral intention and use behavior (Venkatesh et al., 2003). Subsequent validation of UTAUT in longitudinal study by Venkatesh et al., (2003) found that it accounts for 70% of the variance in usage intention, making the UTAUT model a broad, robust and powerful model in technology adoption studies.

Figure 6: *Unified Theory of Acceptance and Use of Technology*



Source: Venkatesh et al., (2003)

Venkatesh et al., (2003) tested the UTAUT model in four different organizational settings for a period of six months and the study showed that three primary constructs; Performance Expectancy, Effort Expectancy and Social Influence, had a significant and direct effect on behavioral intention while Facilitating Conditions and behavioral intention are direct determinants use behavior (Venkatesh et al., 2003; Wang, 2003).

Critics of this model have argued that it is a recent model and therefore requires more validation. Scholars have argued for UTAUT by stating that it is based on a strong theoretical foundation which is as a result of rigorous development process of combining eight models (Schaper and Pervan, 2005, Han et al., 2004). The strength of UTAUT model is in its ability to explain up to 70% of variance (adjusted R^2) Use Behavior, whereas the other models are known to account for between 17% and 53% (Han et al., 2004; Venkatesh et al., 2003). UTAUT also includes aspects of the user‘s characteristics, as well as some prevailing conditions at the time of the possibility to use a certain system or service. Further, by including voluntariness as a moderating factor, it able to account for scenarios where technology adoption is mandatory or voluntary, which is ignored by many other models (Venkatesh et al., 2003).

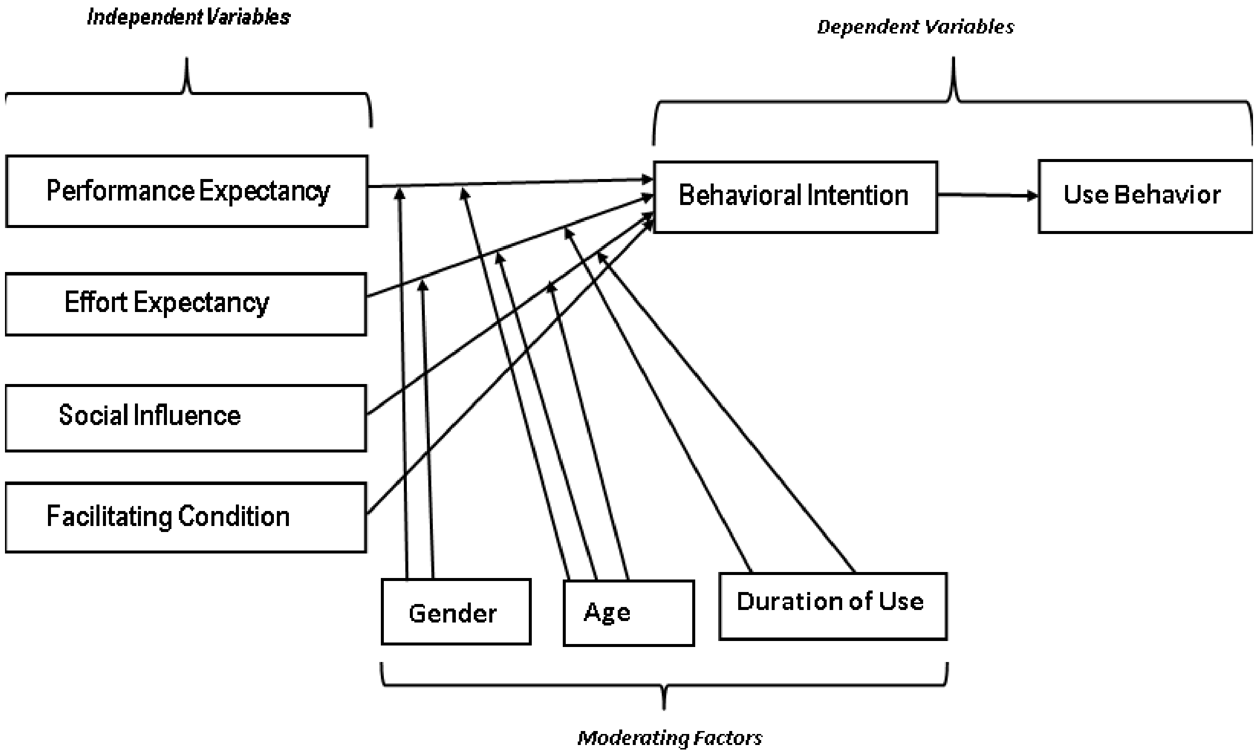
While a lot of literature exist detailing cloud computing adoption, three things are evident; firstly, few studies have used the UTAUT model to investigate the factors influencing cloud computing adoption, even though it presents a superior option based on the fact that it includes other aspects of user characteristics ignored by other model and in addition, it can explain up to 70% of variance in use behavior. Secondly, most of the studies have been conducted mainly in America, Europe, Australia and Japan, China and Taiwan), countries that are evidently advanced in terms of computing technology and internet technology infrastructure permeation. Thirdly, most of the studies have focused on adoption of technologies like online learning, telemedicine, and in the cases where cloud computing issues have been addressed; it has mainly focused on adoption of cloud by corporate organization and institutions and rarely on the individual users.

This model includes facilitating condition as a factor that influences the use of technology. It also includes age, gender and experience as moderator factors to the relationship between the independent and dependent variables. We needed to establish whether facilitating conditions had any influence on behavioral intention to adopt cloud services among students in Kenyan Universities and in addition, to find out the role played by age, gender and duration of use as moderator factors.

2.4 Research Conceptual model:

Based on review of the literature related to technology adoption and technology adoption models and theories, the research conceptual model in Figure 7 below, derived from the UTAUT model was used in this research. Since the research focused on the publicly available cloud computing services where users voluntarily accept and use the available cloud services, the voluntariness was not considered as a moderating factor for the conceptual model.

Figure 7: *Research Conceptual Model*



Source: *Research*

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

This study sought to establish the factors that influence adoption and use of cloud computing services through a conceptual model mainly derived from the UTAUT model (Venkatesh et al., 2003), which incorporate constructs used in other technology adoption theories and model but assuming different names under the respective models. In the conceptual model the primary constructs; Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions are the independent variables, while Behavioral Intention and Use Behavior the dependent variables.

3.1 Research Design

The approach had both quantitative and qualitative dimensions; the quantitative aspect used cross sectional survey design, while the qualitative aspect used focus group discussion. The quantitative approach uses numerical methods and statistical tools for data collection and analysis. The cross sectional survey involved collecting data at one time from the sampled population, which in this study consists of university students from four universities located in Nairobi. The qualitative aspect involved collecting data by engaging in focused group discussion with a group of students to obtain the qualitative aspects of that would help explain certain phenomenon.

3.2 Population

Population is a term that refers to the entire mass of observations; the parent group from which a sample is normally formed (Yogesh, 2006). The study targeted a population of university students at two levels of study - Undergraduate and Postgraduate level, from across four universities; two public universities - University of Nairobi (UoN), The Technical University and two private university – Strathmore University and Catholic University of East Africa (CUEA), all located in Nairobi. The population in this study was roughly 80,000 students.

3.3 Sample

A sample is defined as the number of entities or subjects in a subset of a population selected for analysis. There are several approaches to obtaining and determining the sample size to use in a research. These may include using a census for population that is small, imitating a sample size of similar studies, using published tables, or applying formulas to compute a sample size. According to Mugenda and Mugenda (2003); in the situations where time and resources allow, a research should take as big a sample as possible since this would measure the reliability of the results. Kothari (2004) also points out that an optimum sample is one which fulfills the requirements of efficiency, representativeness, reliability and flexibility.

The level of desired precision and the size of the population are two key factors in determining the sample size. Samples are used when it is not possible or practical to study an entire population Kothari (2004).

In this study, the sample was derived as a function of the population using the formula derived by Yamane (1967:886).

$$n = \frac{N}{1 + N(e)^2}$$

Where:

- **n** = the sample size
- **N** = the population size, and
- **e** = the level of precision.

The population size of the four universities is approximately 80,000, applying the above formula where e = ±7%. The *level of precision (e)*, sometimes called *sampling error*, is the range in which the true value of the population is estimated to be. This range is often expressed in percentage points, which is ±7% in this study.

$$n = 80{,}000/\ (1 + 80{,}000\ (0.07)^2)$$
$$\mathbf{= 204}$$

Sample size = 204 students

3.4 Data Collection: Techniques and Instruments

We considered several options of data collection techniques by examining the ability of the tool to assist in efficiently and effectively collecting the required data, in addition to minimizing bias, cost and duration of data collection. Two techniques were used in data collection for this research; questionnaire and Focus Group Discussion (FGD). The questionnaire method presented a number of advantages: Unlike the interview, it is free from the bias of the interviewer (Kothari, 2004; Singh, 2006). Respondents and for our case university students, who may not be easily approachable, could be reached conveniently. Since it can be used to cover a large geographical area, large samples can be made use of, making the results much more dependable and reliable. Students have adequate time to give well thought out answers. There are several disadvantages as well and these include; Low rate of return of the duly filled in questionnaires and a high possibility of ambiguous replies or omission of replies altogether to certain questions, which presents the difficulty of interpretation of the omissions. There is inbuilt inflexibility because of the difficulty of amending the approach or questions once questionnaires have been dispatched. It also assumes that the intended students are educated, in addition to the difficulty of knowing whether willing students are truly representative.

The research used a 5-part likert-scale-based questionnaire, designed to generate descriptive characteristics on the independent and dependent variables. The 5 point likert scale questionnaire was adopted because of the concern about the ability of the students to differentiate between the different levels in the scale, if wider scale were used.

The questions were made easy to understand and unambiguous for the responders. The questionnaire was designed to capture all possible information on factors influencing adoption and use of cloud computing services as well as to gather statistics on individual characteristics that include age, gender, duration of use, types of cloud services used and frequency of usage. The questionnaire did not include any part that required free text from student (*See Appendix 1*).

The focus group discussion (FGD) was also used in order to get qualitative data that could not be captured through the questionnaire. By asking probing questions, we were able to obtain answers and explanations on some of the quantitative findings.

3.5 Validity of Data Collection Instrument

Validity is defined as the extent to which data collection method/methods accurately measures what they were intended to measure (Saunders et al., 2006). This is supported by

Copper and Schindler (2003) who state that validity refers to the extent to which a test measures what they actually would wish to measure. Generally, validity is concerned with whether the findings are really what they appear to be.

Two forms of validity measures exist; the external validity and internal validity. The external validity refers to the data's ability to be generalized across persons, settings and times. The internal validity on the other hand is the ability of research constructs to accurately measure what is purposed to measure. To ensure internal validity in the study, several measures were taken that include; collecting data from reliable sources i.e. bona fide students from the targeted universities. The survey questionnaire was developed based on extensive and intensive literature review to guarantee validity of the results. It was also pre-tested using 30 students for meaning and semantics and appropriately reviewed by consulted experts and experienced researchers.

3.6 Ethical Consideration

Permission from the administration/authorizing offices of the targeted universities was sought before the data collection began. The university was reassured of privacy and confidentiality. In order to ensure that the prospective student willingly participated in the research, their consent was sought before being asked to participate in the study and they were assured of privacy and confidentiality. The students were requested to exercise honesty when filling the questionnaires. The name field in the questionnaire was optional and was therefore not used in the final data analysis.

3.7 Data Collection Process

The process started by obtaining a formal approval from the administration of the targeted universities. An introductory letter from the office of the deputy director of School of Computing and Informatics of the University of Nairobi and a copy of the questionnaire were submitted to the information/research office of the targeted universities for evaluation and approval. After the approval, the hard copies of questionnaires that were intended for distribution were assigned identification codes and then distributed to students in the targeted universities at random. The coding of questionnaires was to enable the tracking of the distributed questionnaires in order to know the number of questionnaires returned from a given locality. The data collection exercise involved 415 questionnaires that randomly distributed among students in the four participating universities.

3.8 Data cleaning Process

The returned questionnaires were perused for validity by identifying those with errors and discarding them. The errors included incomplete forms especially for the fields that were not optional and those with double or triple responses for a single statements. After identifying valid questionnaires, the data was then code and keyed into Microsoft Excel worksheet data file and then imported into Statistical Program for Social Scientists (SPSS) for detailed analysis.

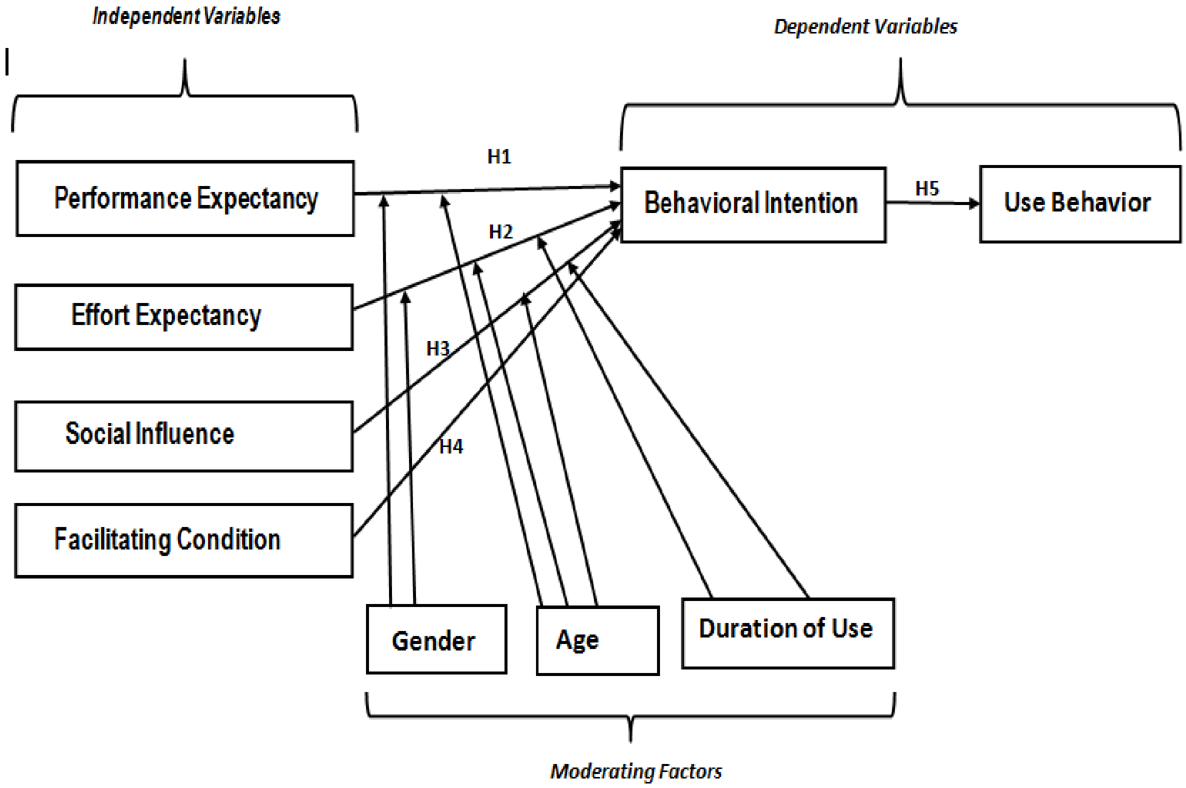
3.9 Reliability

Reliability is defined as an assessment of the degree of consistency between multiple measures of a variable. It is designed to demonstrate the extent to which the operations in a study; data collection procedures can be repeated with similar results. A measure is deemed reliable if an individual's score on the test is the same when given more than once in similar test and under similar circumstances. Several reliability tests were considered. The First method to be considered was the test-retest method. Here, the same questionnaire is re-administered after sometime. The method is resource intensive and time consuming and therefore was considered less suitable for this study, given the time constraints. The second method was the split-half reliability method. This method randomly splits the data set into two. A score of each participant is the calculated based on each half of the scale. If the scale is very reliable, a participant's score on one half of the scale should be the same to their score on the other half, therefore across several participants score from the two halves of the questionnaire should correlate perfectly. A high correlation signifies reliability. This method though slightly better than the test-retest, presented one major challenge; there are several ways of splitting a set of data and the therefore correlation results could be a product of how the data is split. To overcome the problems presented by the first two methods, Cronbach (1951) came up with a measure that is loosely equivalent to splitting data into two in every possible way and computing the correlation coefficient for each. The average value is equivalent to the Cronbach's Alpha coefficient, which is the most common measure of the scale of reliability. This was the reliability measure used in this study. In addition to the fact that it is superior over the split half method, it was selected and used in this study on the strength that it has been successfully applied in many other similar and related studies (Taylor, 2011; Venkatesh et al., 2003; Davis, 1989). The generally agreed upon lower limit for Cronbach's Alpha is 0.7 (Pallant, 2003; Davis 1989).

3.10 Conceptual Model showing Causal Relationship between variables

The research was carried out using the following conceptual model;

Figure 8: *Conceptual Model - Causal relationships*



Source: *Research*

3.11 Hypothesis Formulation

To test the proposed model, five hypotheses were proposed. The hypotheses are stated below.

Performance Expectancy

Venkatesh et al (2003) defined Performance Expectancy as the degree to which an individual believes that using the new technology will help him or her to attain gains in job

performance. They argued that performance expectancy construct is the strongest predictor of Behavioral Intention in both voluntary and mandatory settings. Venkatesh et al (2003) further argued that from a theoretical point of view, there was reason to expect that the relationship between performance expectancy and intention will be moderated by *gender* and *age*. The argument about gender having a moderation effect on the relationship between performance expectancy and behavioral intention was based on findings of the research on gender differences conducted by Minton and Schneider (1980), which suggested that men tend to be highly task-oriented and, therefore, performance expectancies, which focus on task accomplishment, were especially salient to men. In a similar manner, Venkatesh et al (2003) theorized that age would play a moderating role in the relationship between Performance expectancy and Behavioral intention, by basing their argument on the research on job-related attitudes conducted by Hall and Mansfield (1975) and Porter (1963) which suggested that younger workers placed more importance on extrinsic rewards.
We therefore in like manner expect that the influence of performance expectancy on behavioral intention will be moderated by both gender and age.

H1: Performance expectancy is positively associated with the **behavioral intention** and this effect will be moderated by **gender** and **age**, such that the effect will be stronger for men and in particular younger men.

Effort Expectancy

Venkatesh et al (2003) defined Effort expectancy as the degree of ease associated with the use of a new technology or system. They argued that the effort expectancy construct was significant in both voluntary and mandatory usage contexts; however, each was only significant during the first time period, and become non-significant over periods of extended and sustained usage. This, they argued was consistent with previous research findings that included Agarwal and Prasad (1997, 1998), Davis et al. (1989) and Thompson et al. (1991, 1994). Furthermore, by basing their argument on the previous research findings by Davis et al. (1989), Szajna (1996), Venkatesh (1999), Venkatesh and Morris (2000), Bem and Allen (1974) and Bozionelos 1996) they stated that effort-oriented constructs were expected to be more salient in the early stages of a new behavior (technology adoption), and more salient for *women* than for *men*. From research findings by Plude and Hoyer 1985, Venkatesh et al (2003) argued that increased *age* has been shown to be associated with difficulty in processing complex stimuli and allocating attention to information on the job both of which may be necessary when using software systems. Venkatesh et al (2003) also considered other studies that had shown that effort expectancy would be stronger determinants of individuals' intention for women (Venkatesh and Morris 2000; Venkatesh et al. 2000). In a similar manner, we expected that effort expectancy will be stronger for women, particularly those who are older and with relatively little or no experience with the cloud computing services.

H2: **Effort Expectancy** is negatively associated with **behavioral intention** and this effect will be moderated by **gender**, **age**, and **experience**, such that the effect will be stronger for females, particularly younger females, and particularly at early stages of experience.

Social Influence

Venkatesh et al (2003) defined Social influence as the degree to which an individual perceives that important others believe he or she should use the new system. Based on the findings of Venkatesh and Davis (2000), Venkatesh et al (2003) argued that Social influence is a direct determinant of behavioral intention and suggested that such effects could be attributed to compliance in mandatory contexts that causes social influences to have a direct effect on intention; in contrast, social influence in voluntary contexts which operates by influencing perceptions about the technology. In mandatory settings they argued; social influence appears to be important only in the early stages of individual experience with the technology, with its role eroding over time and eventually becoming non-significant.

Basing their argument on previous research findings by French and Raven (1959), Warshaw (1980) and Hartwick and Barki (1994), Venkatesh et al (2003) suggested that individuals were more likely to comply with others' expectations when those referent others have the ability to reward the desired behavior or punish non-behavior and furthermore, that reliance on others' opinions is significant only in mandatory settings particularly in the early stages of experience, when an individual's opinions are relatively ill-informed. By drawing from other prior studies by Miller (1976), Venkatesh et al. (2000) and Venkatesh and Morris 2000), Venkatesh et al (2003) suggested that older worker and particularly women tended to be more

sensitive to others' opinions and therefore find social influence to be more salient when forming an intention to use new technology, with the effect declining with experience.
Even though Vankatesh et al (2003) argues that in a voluntary context, social influence only influences perception, we seek to investigate the effect of lecturer, peer influence and other forms of social influence towards adoption of cloud services.

H3: Social Influence is positively associated with behavioral intention and this effect will be moderated by **gender**, **age** and **experience**, such that the effect will be stronger for women, particularly older women in the early stages of initial usage.

Facilitating Conditions

In technology adoption studies, facilitating conditions is defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the new technology (Venkatesh et al., 2003). By basing their argument on the findings by Bergeron et al. (1990), they suggested that when organizational and technical infrastructure exists to support use of a new technology, users are likely to use the technology. Furthermore, the effect of facilitating conditions was likely to increase with experience as users of technology find multiple avenues for help and support throughout the organization, thereby removing impediments to sustained usage. Drawing from the findings of Hall and Mansfield (1975) they further suggested that that older workers attach more importance to receiving help and assistance on the job. They concluded that, when moderated by experience and age, facilitating conditions will have a significant influence on usage behavior. In this study, we sought to establish the effect of facilitating condition on behavioral intention.

H4: **Facilitating conditions** will not have any significant influence on **behavioral intention**

Use Behavior

From the UTAUT model, Venkatesh et al (2003) argued that consistent with the underlying theory for all of the intention models; behavioral intention directly influenced use behavior. We expect that behavioral intention will have a significant positive influence on technology usage.

H5: **Behavioral Intention** will have a significant influence on **use behavior.**

3.12 Construct Measures

Performance Expectancy

In order to directly measure the students' opinion on the usefulness of the cloud computing services, Performance Expectancy was measured using four statements.

- **PE1**: I find cloud computing service(s) useful in my tasks
- **PE2:** Using cloud computing service(s) enable me to accomplish tasks more quickly
- **PE3:** Using cloud computing service(s) increases my productivity
- **PE4:** Using cloud computing service(s) is convenient to me

Effort Expectancy

To measure the effort in relation to using cloud computing services, Effort Expectancy was measured using four statements;

- **EE1**: My interaction with cloud computing service(s) is clear and understandable
- **EE2**: It is easy for me to become skillful at using cloud computing service(s)
- **EE3**: I find cloud computing service(s) easy to use
- **EE4**: Learning to operate cloud computing service(s) is easy for me

Social Influence

The social influence was measured using four statements;

- **SI1:** Classmates who influence my behavior think that I should use cloud computing service(s)
- **SI2:** Friends who are important to me think that I should use cloud computing service(s)
- **SI3**: My lectures have encouraged me to use of cloud computing service(s)
- **SI4**: My peers have encouraged me to use of cloud computing service(s)

Facilitating Condition:

Facilitation condition was measured using four statements;

- **FC1:** I have the resources (financial – Money to purchase air time) and/or equipment – modem and laptop/notebook) necessary to use cloud computing service(s)
- **FC2:** I have the knowledge necessary to use cloud computing service(s)
- **FC3:** Cloud computing service(s) is not compatible with the university systems (internet access system and associated applications) I use

- **FC4:** There are people available for assistance with cloud computing service(s) difficulties

Behavioral Intention
Behavioral intention was measured using three statements;

- **BI1**: I intend to continue using cloud computing services
- **BI2**: I predict I would continue to use cloud computing services
- **BI3**: I will always use cloud computing services

3.13 Data Analysis

Two techniques; partial correlation and focus group discussion were used for data analysis.

Partial Correlation:

In research, it may at times be desirable to know or estimate the relationship or association between two variables; a predictor variable and a criterion or outcome variable. In order to see the actual relationship or association between the variables without the influence of other variables, controlling for the effects of other variables is necessary. The effects of the other variables on the relationship or association between the predictor variable and the criterion are eliminated when they are held constant. This process of exercising statistical control is known as partialing or residualization. A partial correlation or Partialing measures the degree of association between two variables that would exist if all influences of one or more other variables could be removed. The purpose is to find the unique variance between two variables while eliminating the variance from a third variable. The Pearson partial correlation between two variables, after controlling for variables in the partial statement, is equivalent to the Pearson correlation between the residuals of the two variables after regression on the controlling variables. We chose partial correlation technique in order to establish the degree of association between primary constructs (independent variables) and Behavioral intention (dependent variable).

Focus Group Discussion (FGD)

A technique used to collect qualitative data. This is where a group of individuals from among the students that are participating in a study engage in discussion under the guidance of the researcher, in order to generate certain information that the researcher deems critical in explaining certain results from the study. The overall aim is to capture certain qualitative aspects of the study in greater details in order to explain certain phenomenon. We selected FGD because of its ability to generate certain data that could not be captured through the questionnaire or which would have taken too long using other methods like interview.

CHAPTER 4: RESULTS AND DISCUSSION

4.0 Introduction

This chapter focuses on the results and analysis. SPSS version 16.0 software complimented by MS excel was used for analysis of data.

4.1 Response rate

Out of the 415 questionnaires distributed, 217 were found valid for use in the analysis process.

4.2 General Characteristic of the Students

The students were categorized into age groups and their level of study. **Table 1** shows the statistics. The age group 19 years to 24 years accounted for 52.5% of the total number of students. Out of the 52.5%, of the total number of students, the postgraduate students accounted for 5.3%, which translates to 6 students, while the undergraduate students accounted 94.7%, which translates to 108 students. The 25 years to 30 years age group accounted for 25.8% of the total number of students, where the postgraduate were 66.1% while the undergraduates were 33.9%. The contribution of the 31 years to 36 years age group to the overall number of students was 14.3%, where the postgraduate were 93.5% while the undergraduate were 6.5%. The 37 years to 42years age group accounted for 6% of the total number of students, where 92.3% were postgraduates and 7.7% being the undergraduate students. The age group with students who were 43 and above accounted for 1.4% of the overall number of students of the study. The results tend to suggest that most undergraduate fall in the 19 years to 24 years age group while the postgraduate students are 30 years and above.

Table 1: *Age group and level of study characteristics*

Number of Students	Overall (%)	Age Group	Postgraduate (%)	Undergraduate (%)	Total (%)
114	52.5	19 - 24	5.3	94.7	100
56	25.8	25 - 30	66.1	33.9	100
31	14.3	31 - 36	93.5	6.5	100
13	6.0	37 - 42	92.3	7.7	100
3	1.4	43+	100	0	100
217	100	Total	40.1	59.9	100

Source: *Research*

The results were also analyzed to obtain the overall distribution of students as well as gender distribution across the targeted universities. As shown in table 2, results indicate that University of Nairobi accounted for most of the students with 152 students, Strathmore University had 45 students, Catholic University of East Africa had 1, while The Technical University of Kenya had 19 students. University of Nairobi accounted for most of the students in both genders; 99 male and 53 females.

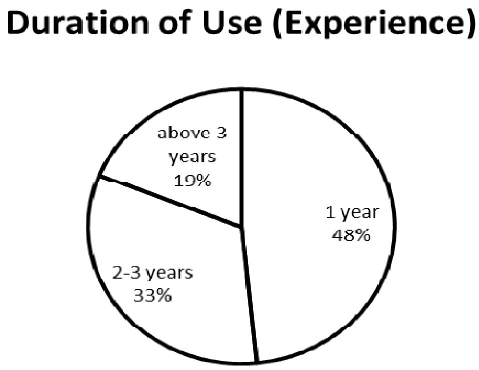
Table 2: *Institution and gender characteristics*

Institution of study	No. of Students	Gender				Total (%)
		Male		Female		
		No.	(%)	No.	(%)	
University of Nairobi	152	99	45.7%	53	24.4%	70.1%
Strathmore University	45	23	10.6%	22	10.1%	20.7%
Catholic University of East Africa	1	1	0.5%	0	0%	0.5%
Kenya Polytechnic University College	19	13	5.9%	6	2.8%	8.7%
Total	217	136	62.7%	81	37.3%	100%

Source: *Research*

The results were organized and then categorized based on the duration that the students had been using cloud computing services. Those with experience of up to 1 year were 48%, those with experience of 2 years to 3 years accounted for 33% while those with experience of more than 3 years accounted for the remaining 19%. Figure 9 show the results of the analysis of duration of usage.

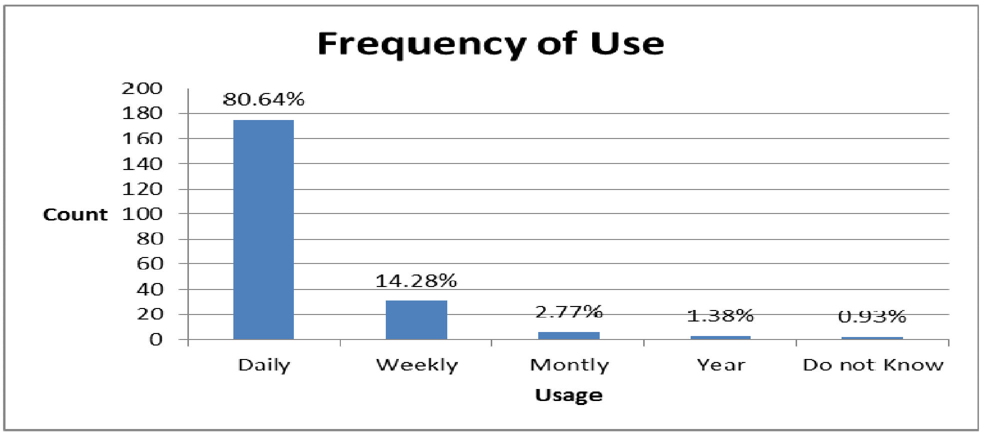
Figure 9: *Duration of usage of Cloud Services*



Source: *Research*

The frequency of use statistics shown in **figure 10** indicates that 80.64% of the students were using the cloud services on a daily basis and this translates to 175 of the total students in the study. Those who use the services weekly were 31 students, which translated to 14.28% of the total number of students. The remaining 5.08% accounted for the monthly, yearly and those users who were unable to tell how frequent they used the services. We observed that most students were daily users of cloud services.

Figure 10: *Frequency of Usage statistics*



Source: *Research*

Service Utilization

The cloud services were grouped into three major categories; SaaS, PaaS and IaaS. The instances of usage were computed and the overall level of services usage percentage extracted. The results in table 3 suggested that SaaS was the most utilized cloud service at 72.9%, followed by IaaS 21.68% and finally PaaS at 5.42%.

Table 3: *Services and service utilization level*

Service Category	Services Type	Responses	Total instances of use
SaaS	Google Docs	152	444
	YouTube	148	
	Email	144	
PaaS	Google Apps Engine	30	33
	Windows Azure	3	
IaaS	Dropbox	69	132
	Sendspace	26	
	Sky Drive	24	
	Ubuntu-one	13	

Source: *Research*

4.3 Descriptive statistics of the independent variables

Analysis of responses for constructs measuring statements

A summary of the responses for the measure statements for each construct was computed on statement by statement basis. The likert scale in the questionnaire had five levels; Disagree, Disagree Somewhat, Neutral, Agree Somewhat and Agree. The responses for Disagree and Disagree Somewhat were summed up and presented as Disagree. The responses for Agree Somewhat and Agree were also summed up and presented as Agree, while the responses of Neutral were left as Neutral. The final output shows three measures; Disagree, Neutral and Agree (*See table 4 below*).

Table 4: Responses Analysis Scale

Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree
The two combined to form "**Agree**"		Neutral	The two combined to form "**Disagree**"	

Source: *Research*

Performance Expectancy

The students were asked to indicate their level of agreement with four statements of performance expectancy. Table 5 shows the results and response levels associated with each measure statement.

Table 5: *Response Analysis for Performance Expectancy measure*

Performance Expectancy		Statistics of Agreement or disagreement with Statements			
Item		Disagree	Neutral	Agree	Total (%)
PE1	I find cloud computing service(s) useful in my tasks.	0.5%	1.8%	97.7%	100%
PE2	Using cloud computing service(s) enable me to accomplish tasks more quickly	2.3%	4.6%	93.1%	100%
PE3	Using cloud computing service(s) increases my productivity.	1.8%	4.1%	94.1%	100%
PE4	Using cloud computing service(s) is convenient to me	2.3%	2.3%	95.4%	100%

Source: *Research*

The students were first asked whether they found cloud computing services useful to in their tasks. A high percentage of students (97.7%) agreed, a small percentage of users (0.5%) disagreed while the remaining students (1.8%) could neither agree nor disagree. Therefore, for most of the students, using the cloud computing services found the services useful in their tasks.

The students were then presented with a second statement that was aimed at establishing; whether the cloud computing services enabled the students to accomplish their tasks more quickly. Out of all students 93.1% agree, 2.3% disagree while 4.6% remained neutral. The results tend suggest that most users found that cloud services enabled them to accomplish their tasks more quickly.

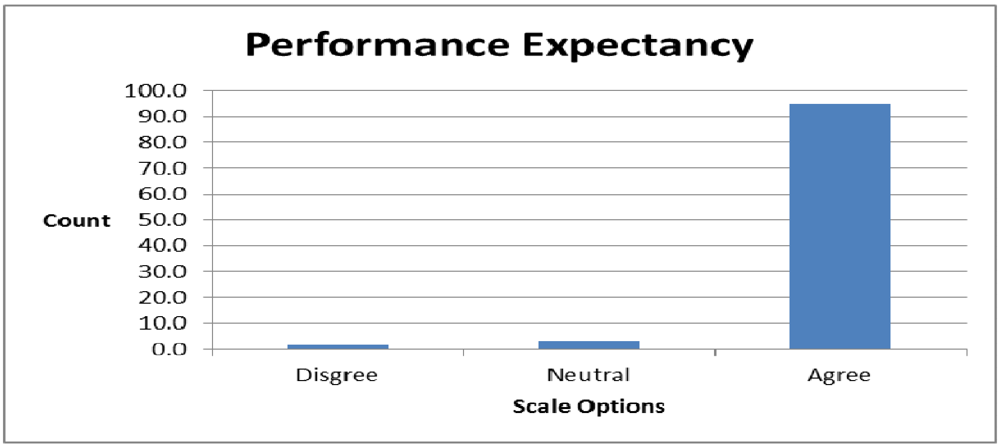
The students were further asked whether using cloud computing services increased their productivity. The results show that 94.1% agreed, 1.8% disagreed while 4.1% were neutral. This is an indication that most students' productivity increased when they used cloud computing services.

Finally, they were asked whether they found cloud services convenient. Table 4 shows that 95.4% of the users agree, 2.3% are neutral and the remaining 2.3% disagree. From the results, it is evident that the students find the cloud services convenient.

Figure 11 shows a summary of the overall response for the performance expectancy construct, an indication that users generally find cloud computing services useful

The overall response for the performance expectancy statements showed that 1.7% of the students disagreed, 3.2% were neutral while 95.1% of the total number of students agreed with the measure statements.

Figure 11: *Response Summary - Performance Expectancy*



Source: *Research*

Effort Expectancy

Effort Expectancy measure was designed to capture data related to effort that the user has to exert in order to use cloud computing services and how the level of effort exerted influences adoption and use of cloud computing services.

Table 6: *Response Analysis for Effort Expectancy Measure*

Effort Expectancy		Statistics of Agreement with Statements			
Item		Disagree	Neutral	Agree	Total (%)
EE1	My interaction with cloud computing service(s) is clear and understandable	19.4%	6.5%	74.1%	100%
EE2	It is easy for me to become skillful at using cloud computing service(s).	18.4%	8.8%	72.8%	100%
EE3	I find cloud computing service(s) easy to use.	17.5%	8.3%	74.2%	100%
EE4	Learning to operate cloud computing service(s) is easy for me	18.1%	6.0%	75.9%	100%

Source: *Research*

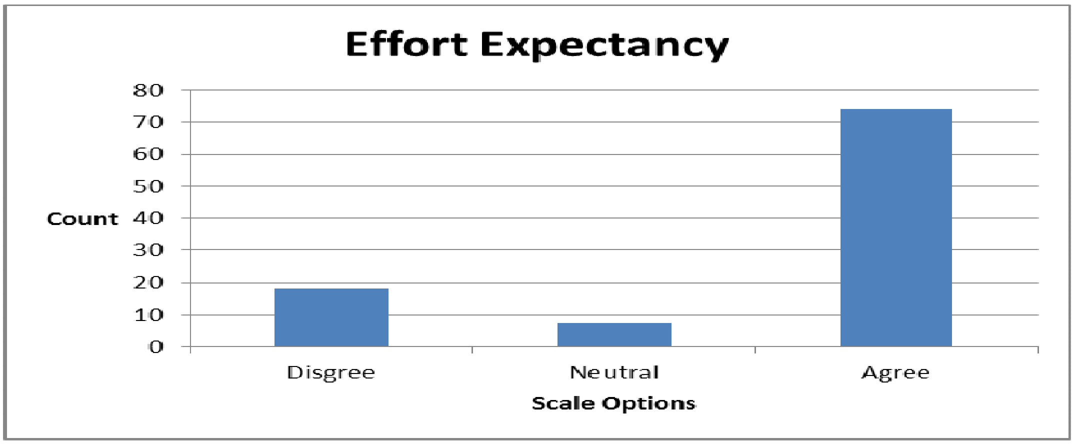
To establish this, the students were first asked whether their interaction with cloud services was clear and understandable. From table 6, 74.1% agree, 6.5% remained neutral and 19.4% disagree. This response statistics suggest that a high number of the students have good knowledge of the usage of cloud computing services.

The students were then asked whether it was easy to become skillful at using cloud computing services; 72.8% agree, 18.4% disagree and 8.8% are neutral. A high percentage of those who were in agreement is an indication that the average university student in the sampled university does not find the process of skilling up on how to use cloud computing services a hindrance. The students were further asked whether using cloud computing services was easy; 74.2% agree, 17.5% disagree and 8.3% are neutral.

Finally, the students were asked whether learning to operate cloud computing services was easy for them. Table 6 shows that 75.9% agree, 6.0% are neutral and 18.1% disagree. The high levels of agree is an indication that it is relatively easy for the students to operate cloud computing services, which is a confirmation of the first three statements.

The overall response for the effort expectancy measure statements indicated that 18.4% of the students disagreed, 7.4% were neutral while 74.3% of the total number of students agreed.

Figure 12: *Summary of responses - Effort Expectancy*



Source: *Research*

Social Influence

The social influence variable was designed to capture data on the social influence, in an attempt to establish its role in the adoption of cloud computing services among university students in Kenya. To establish this, the students were presented with four statements and asked to indicate their levels of agreement with each of the statements.

Table 7: *Response Analysis for Social Influence Measure*

Social Influence		Statistics of Agreement with Statements			
Item		Disagree	Neutral	Agree	Total (%)
SI1	People who influence my behavior think that I should use cloud computing service(s)	28.1%	17.1%	54.8%	100%
SI2	People who are important to me think that I should use cloud computing service(s).	27.8%	23.6%	48.6%	100%
SI3	My lectures have encouraged me to use of cloud computing service(s).	47.5%	13.5%	39%	100%
SI4	My peers have encouraged me to use of cloud computing service(s).	17.6%	14.40%	68%	100%

Source: *Research*

The students were first asked whether people who influence their behavior think that they should use cloud computing services. Table 7 shows the responses; 54.8% agree, 17.1% are neutral and 28.1% disagree, an indication that there is some degree of influence.

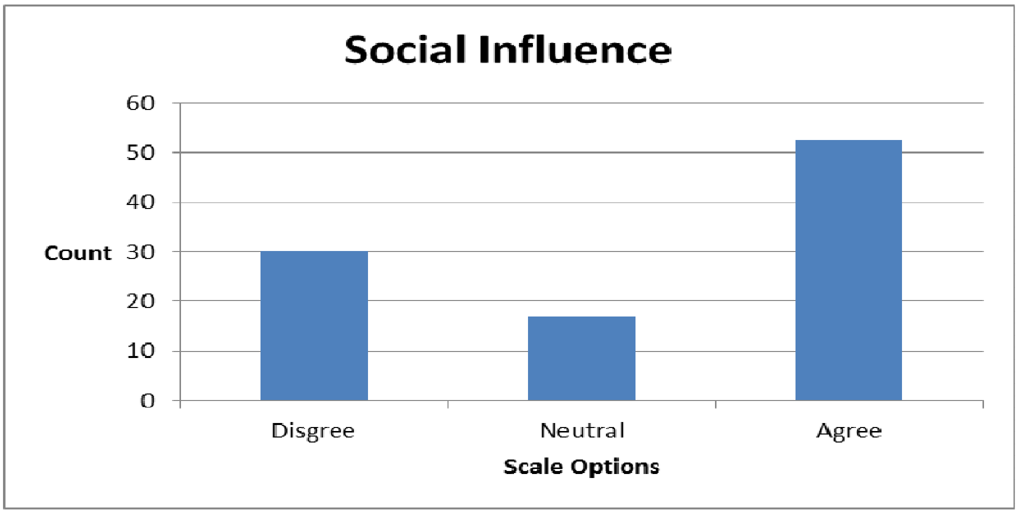
The students were then asked whether people who are important to them think that they should use cloud computing services; 48.6% agree, 27.8% disagree and 23.6% are neutral. This shows important people in the students' life have a slight influence on the students' adoption and use of cloud computing services.

The students were further asked whether their lecturers encouraged them to use cloud computing services; 39% agree, 13.5% are neutral and 47.5% disagree, an indication that ***the influence of the lecturer on the student with regard to use of cloud computing is minimal***.

The students were finally asked whether their peers encouraged them to use cloud computing services. The responses from table 7 indicate that 68% agree, 17.6% disagree and 14.4% are neutral. This is a pointer to the fact that there is a significant level of peer influence among the university students towards the use of cloud computing services. Figure 13 is a summary of the responses regarding Social Influence towards use of cloud computing services.

The overall response for the social influence statements showed that 30.3% of the students disagreed, 17.2% were neutral while 52.6% of the total number of students agreed with the measure statements.

Figure 13: *Response Summary - Social Influence*



Source: *Research*

Facilitating Conditions

The facilitating conditions measure was designed to generate statistics about the environment in the universities and how the prevailing environment influences the adoption and use of cloud computing services. In order to collect data related to this, the student was presented with four statements that required them to indicate their level of agreement with each.

First, they were asked whether they had the resources both financial and equipment that were necessary to use cloud computing services. Table 8 presents the responses; 77.4% of the students agree, 8.3% disagree and 14.3% indicated neutral. The high percentage of agree on this statement suggests that most students have an environment that is conducive for accessing and using cloud computing services.

Table 8: *Response Analysis for Facilitation Condition Measure*

Facilitating Condition		Statistics of Agreement with Statements		
Item		Disagree	Neutral	Agree
FC1	I have the resources (financial and/or equipment) necessary to use cloud computing service(s)	8.3%	14.3%	77.4%
FC2	I have the knowledge necessary to use cloud computing service(s).	2.8%	6.9%	90.3%
FC3	Cloud computing service(s) is not compatible with the university systems I use.	16.1%	19.4%	64.5%
FC4	There are people available for assistance with cloud computing service(s) difficulties.	35.9%	25.3%	38.8%

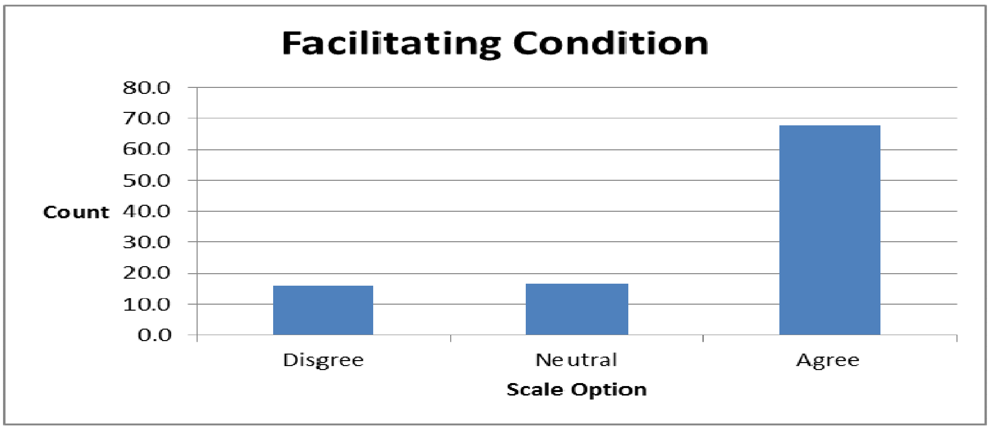
Source: *Research*

The students were then asked if they had the necessary knowledge to use cloud services; 90.3% agree, 6.9% neutral and 2.8% disagree. From the responses, it is evident that most students have the necessary knowledge to use cloud computing services.

Further, the students were asked whether cloud computing services were compatible with the university system. The responses shows that 64.5% agree, 16.1% disagree and 19.4% of the students indicated neutral. The result tends to suggest that the university systems are fairly compatible with the cloud services. The students were finally asked whether there were people available to assist with cloud computing difficulties; 38.8% agree, 35.9% disagree and the remaining 25.3% indicated neutral. ***The percentages suggest that there is minimal assistance available with regard to use of cloud computing services at the universities***. The summary of the responses presented in figure 14 show that the facilitating condition is not a hindrance to adoption and usage of cloud services for the university students.

The overall response for the facilitating condition statements showed that 15.8% of the students disagreed, 16.5% were neutral while 67.8% of the total number of students agreed with the measure statements.

Figure 14: *Response Summary - Facilitating Condition*



Source: *Research*

Behavioral Intention

In order to capture data on behavioral intention, the students were presented with three statements and asked to indicate their level of agreement with each. The students were first asked if they intend to continue using cloud services. Table 9 shows that 99.1% agree, 0.1% disagrees and 0.9% responded indicating neutral. This is an indicator that the students intended to continue using cloud services.

Table 9: *Response Analysis for Behavioral Intention Measure*

Behavioral Intention		Statistics of Agreement with Statements		
Item		Disagree	Neutral	Agree
BI1	I intend to continue using cloud computing services	0.1%	0.9%	99%
BI2	I predict I would continue to use cloud computing services.	1.8%	0.9%	97.3%
BI3	I will always use cloud computing services.	1.4%	5.5%	93.1%

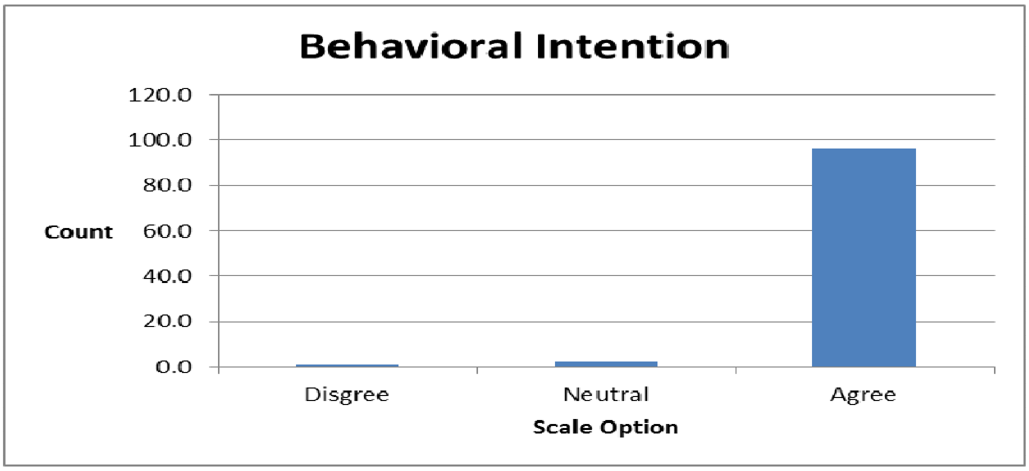
Source: *Research*

The students were further asked if they predict that they will continue using cloud services; 97.3% agreed, 1.8% responded with disagreement while 0.9% was neutral. The high percentages for agree suggest that the probability that the students will continue using cloud services was high.

The students were finally asked if they will always use cloud computing services; 93.1% agree that they will always continue using the cloud services, 1.4% disagree and 5.5% gave the neutral response. The high rate of agree in the three statements suggest that the users have the intention to continue utilizing cloud computing services and this is confirmed by the overall summary of responses in figure 15.

The overall response for the behavioral intention statements showed that 1.1% of the students disagreed, 2.4% were neutral while 96.5% of the total number of students agreed with the measure statements.

Figure 15: *Response Summary - Behavioral Intention*



Source: *Research*

4.3 Pearson Correlation statistics

Pearson correlation measures the relationship between the independent variables and dependent variables where Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Condition (FC) are the independent variables while Behavioral Intention (BI) is the dependent variable.

To establish the correlation between the independent variables and the dependent variables in this study, Pearson Correlation Coefficients for each independent and dependent variables were computed.

The measure of association between two variables using Pearson correlation coefficient reports 3 aspects: First, it reports on the strength of the association. The scale used has values ranging from negative 1 (-ve), through "0" to positive 1 (+ve). When the Pearson correlation Coefficients has a value closer to Positive (+ve) or Negative (-ve) 1, then the association or correlation is said to be strong. A value closer to 0 on either side indicates a weak relationship. Secondly, it reports on the direction; the direction can either be positive (+ve) or Negative (–ve). Positive (+ve) means that an increase in independent variable values causes an increase in associated dependent variable values (Scores). On the other hand, negative (-ve) direction means that when there is a rise in values in one variable, it causes the values of the associated variable to decrease. The variable are said to have an inverse relationship. Finally, it reports on the significance; when the value of significance is less than 0.05 the correlation is significant, while on the other hand when the value is greater than 0.05 the correlation is not significant.

In situations where it is suspected that the association between independent and dependent variables is being influenced by other factors either directly or indirectly, there may be need to eliminate the influence of these factors on the relationship in order to get a clearer and more accurate indication of the relationship or association between the two variables. This is achieved by statistically removing the influence of the confounding factor.

Correlation between Independent and Dependent Variables

In table 10, the Pearson correlation coefficient between the performance expectancy (PE) and behavioral intention (BI) is positive and significant at 0.315**. This is means that increases in the students' performance expectancy results in a corresponding rise in behavioral intention to accept and use cloud computing services. The correlation between effort expectancy and behavioral intention is negative and weak at -0.044 (-ve). Effort expectancy and behavioral intention have an inverse relationship, where a rise in the effort expectancy results in a drop in the behavioral intention. The result is not significant because the value of significance (2-tailed) is 0.525, which is more than 0.05. The correlation between social influence and behavioral intention has a Pearson correlation coefficient of -0.007, signifying a negative and very weak association between these two variables. The correlation is not significant because the value of the significance (2-tailed) component exceeds 0.05. The Pearson correlation coefficient for the correlation between facilitating condition and behavioral intention is 0.227**, an indication that the association between these two variables is positive. The significance (2-tailed) is 0.001 which is less than 0.05 threshold and hence the association is significant.

Table 10: *Pearson Correlation between Independent and dependent variables*

Pearson Correlation Between Independent and Dependent Variables		
Independent Variables	Correlation Coefficient & Significance Measure	Dependent Variable Behavioral Intention (BI)
Performance Expectancy (PE)	Pearson Correlation	0.315**
	Sig. (2-tailed)	0.000
Effort Expectancy (EE)	Pearson Correlation	-0.044
	Sig. (2-tailed)	0.525
Social Influence (SI)	Pearson Correlation	-0.007
	Sig. (2-tailed)	0.920
Facilitating Conditions (FC)	Pearson Correlation	.227**
	Sig. (2-tailed)	0.001
**. Correlation is significant at the 0.01 level (2-tailed).		

Source: *Research*

Correlation for PE and BI with control Variables

The correlation between the performance expectancy and behavioral intention with control variables; age, gender and duration of usage are shown in table 11. The correlations between PE and BI with age, gender and duration of use as control variables are; +0.319, +0.311 and +0.318 respectively. Positive correlation coefficient in all the above cases is an indicator of a direct relation between the two variables; an increase in PE leads to an increase in BI. Based on this, the correlation between EF and BI is positive and strong. The significance (2-tailed) values are more than the threshold of 0.05 in all the cases and this makes the association insignificant.

Table 11: *Pearson Correlation for **PE** and **BI** with control Variables*

Pearson correlations between IV & DV, with Control Variables			
Performance Expectancy (Independent Variable) and Behavioral Intention (Dependent)			
Control Variables		Pearson Coefficient	BI
• Gender	PE	Correlation	0.319
		Significance (2-tailed)	0.000
• Age	PE	Correlation	0.311
		Significance (2-tailed)	0.000
• Duration of Usage (Experience)	PE	Correlation	0.318
		Significance (2-tailed)	0.000
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

Correlation for EE and BI with control Variables; Age, Gender and Duration of use

Table 12 shows the correlations between effort expectancy and behavioral intention, with age, gender and duration of use as the control variables.

Table 12*: Pearson Correlation for EE and BI with control Variables*

Effort Expectancy (Independent Variable) and Behavioral Intention (Dependent)			
Control Variables		Pearson Coefficient	EE
• Age	EE	Correlation	-0.033
		Significance (2-tailed)	0.626
• Gender	EE	Correlation	-0.065
		Significance (2-tailed)	0.342
• Duration of Usage (Experience)	EE	Correlation	-0.054
		Significance (2-tailed)	0.428
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

The correlations between EE and BI with age, gender and duration of use as control variables are; -0.033, -0.065 and -0.054 respectively. The negative correlation coefficient values in all the above cases are an indicator of an inverse relation between EE and BI. Given that the values are much lower than the highest possible value of -1 (on the negative side), the correlation between EE and BI is weak and negative. The significance (2-tailed) values are more than the threshold of 0.05 and this makes the association insignificant.

Correlation for SI and BI with control Variables; Age, Gender and Duration of use

The correlation between the Social Influence and behavioral intention with control variables; age, gender and duration of usage are shown in table 13. The correlations between SI and BI with age, gender and duration of use as control variables are; -0.01, -0.001 and -0.014 respectively. Negative correlation coefficient in all the cases here is an indicator of an inverse relation between the two variables. Given that the values are far from the maximum -1, the correlation between SI and BI is weak and negative. The significance (2-tailed) values are more than the threshold of 0.05 and this makes the association not significant.

Table 13*: Pearson Correlation for SI and BI with control Variables*

Social Influence (Independent Variable) and Behavioral Intention (Dependent)			
Control Variables		Pearson Coefficient	BI
• Gender	SI	Correlation	-0.01
		Significance (2-tailed)	0.885
• Age	SI	Correlation	-0.001
		Significance (2-tailed)	0.984
• Duration of Usage (Experience)	SI	Correlation	-0.014
		Significance (2-tailed)	0.838
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

Correlation for FC and BI with control Variables

The Pearson correlation coefficients of the association between facilitating condition and behavioral intention with age, gender and duration of use as control variables are shown in table 14. The correlations between SI and BI with age, gender and duration of use as control variables are; +0.223, +0.228 and +0.225 respectively. The positive correlation coefficient in all the cases here is an indicator of a direct relation between the two variables; an increase in the value of FC leads to an increase in the value of BI. Based on this, the correlation between SI and BI is positive and strong. The significance (2-tailed) values are less than the threshold of 0.05 and this makes the association significant.

Table 14*: Pearson Correlation for FC and BI with control Variables*

Facilitating Condition (Independent Variable) and Behavioral Intention (Dependent)			
Control Variables		Pearson Coefficient	FC
• Gender	FC	Correlation	0.228
		Significance (2-tailed)	0.001
• Age	FC	Correlation	0.223
		Significance (2-tailed)	0.001
• Duration of Usage	FC	Correlation	0.225
		Significance (2-tailed)	0.001
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

Correlation for PE and BI with age and gender as control Variables

Table 15 shows the results of correlation when both age and gender are control variables. The results are positive and significant, an indication that a rise in PE will result in a rise in BI.

Table 15*: Pearson Correlation for* ***PE*** *and* ***BI*** *with Gender and Age as control Variables*

Performance Expectancy (Independent Variable) and Behavioral Intention (Dependent), with Control Variables			
Control Variables: Gender & Age			BI
	PE	Correlation	0.315
		Significance (2-tailed)	0.000
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

Correlation for FC and BI with age, gender and duration of use as control Variables

The correlation between FC and BI, with age, gender and duration as control variables is shown in table16. The association is positive and significant, an indication that better facilitating conditions would lead to a rise in the behavioral intention to use cloud computing services.

Table 16: *Pearson Correlation: FC & BI with Age, Gender & Duration of use as control Variables*

Facilitating Condition (Independent Variable) and Behavioral Intention (Dependent), with Control Variables			
Control Variables: Duration of Usage & Gender & Age		Pearson Coefficient	BI
	FC	Correlation	0.224
		Significance (2-tailed)	0.001
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: *Research*

Table 17 shows a summary of correlation between independent variables and the dependent variables when age and gender are the control variables.

Table 17: *Pearson Correlations for PE, EE, SI, FC and BI with control variables; Age & Gender*

Correlations						
Control Variables			PE	EE	SI	FC
Age & Gender	PE	Correlation	1.000	0.066	-0.004	0.234
		Significance (2-tailed)	.	0.337	0.954	0.001
	EE	Correlation	0.066	1.000	0.308	0.084
		Significance (2-tailed)	0.337	.	0.000	0.224
	SI	Correlation	-0.004	0.308	1.000	0.164
		Significance (2-tailed)	0.954	0.000	.	0.017
	FC	Correlation	0.234	0.084	0.164	1.000
		Significance (2-tailed)	0.001	0.224	0.017	.
	BI	**Correlation**	**0.315**	**-0.054**	**-0.005**	**0.302**
		Significance (2-tailed)	**0.000**	**0.437**	**0.947**	**0.047**

Source: *Research*

Table 18 shows a summary of the correlations between the independent and the dependent variables when age, gender and duration of use are the control variables.

Table 18: *Pearson Correlations for PE, EE, SI, FC and BI with Control Variables – Age, Gender and Experience*

Correlations						
Control Variables			**PE**	**EE**	**SI**	**FC**
Age, Gender & Duration of Use	PE	Correlation	1.000	0.070	0.001	0.266
		Significance (2-tailed)	.	0.312	0.991	0.000
	EE	Correlation	0.070	1.000	0.299	0.215
		Significance (2-tailed)	0.312	.	0.000	0.002
	SI	Correlation	0.001	0.299	1.000	0.075
		Significance (2-tailed)	0.991	0.000	.	0.277
	FC	Correlation	0.266	0.215	0.075	1.000
		Significance (2-tailed)	0.000	0.002	0.277	.
	BI	**Correlation**	**0.315**	**-0.056**	**-0.008**	**0.224**
		Significance (2-tailed)	**0.000**	**0.416**	**0.906**	**0.001**

Source: *Research*

4.4 Analysis of Effects of Moderating factors on Primary factors

Cross tabulation between the independent variables and each moderating factor was done to establish how each moderating factor influences the association between the independent and dependent variable. Age limit was defined in order to create a distinction between the young and the old. Young was defined as the age below 36 years while old was any age above 36 years.

Table 19 shows cross tabulation between gender and performance expectancy; higher numbers of males gave a response of agree, an indication that they find cloud computing services convenient and useful in accomplishing of tasks.

Table 19: *Cross tabulation between Gender and performance expectancy*

Gender * Performance Expectancy Cross tabulation						
			Disagree	Neutral	Agree	Total
Gender	Male	Count	4	4	128	136
		% within Gender	2.9%	2.9%	94.1%	100.0 %
	Female	Count	1	1	79	81
		% within Gender	1.2%	1.2%	97.5%	100.0 %
	Total	Count	5	5	207	217
		% within Gender	2.3%	2.3%	95.4%	100.0 %

Source: Research

The result of cross tabulation between age and performance expectancy are shown in table 20. It is evident that there are more students below the age of 36 who agree that cloud computing services are convenient, useful and contribute positively towards accomplishment of tasks.

Table 20: *Cross tabulation between age and performance expectancy*

Age * Performance Expectancy (Cross tabulation)						
Age		Disagree	Neutral	Agree	Total	Aver: Young/Old
19 -24	Count	4	4	106	114	Young: 96% of all the young agree
	(%)	3.5%	3.5%	93.0%	100.0%	
25-30	Count	0	1	55	56	
	(%)	0.0%	1.8%	98.2%	100.0%	
31-36	Count	0	0	31	31	
	(%)	0.0%	0.0%	100.0%	100.0%	Old: 93.5% of all the old agree
37-42	Count	0	0	13	13	
	(%)	.0%	.0%	100.0%	100.0%	
43+	Count	1	0	2	3	
	(%)	33.3%	.0%	66.7%	100.0%	
Total	Count	5	5	207	217	
	(%)	2.3%	2.3%	95.4%	100.0%	

Source: *Research*

The results show that 106 (93%) of students between the ages 19 years to 24 years agree, 55

(98.2%) in the ages between 25 years to 30 years agree and 31 (100%) of students between the ages of 31 years to 36 agree. The combined responses shows that 96% of all the young (ages: 19 years to 36 years) agree with the performance expectancy statements compared to 93.5% of the old (Ages above 36 years), which implies that the performance expectancy is stronger for the younger students.

The cross tabulation between gender and effort expectancy in table 21 is designed to show the effect of gender on effort expectancy as relates to the adoption and use cloud computing services.

Table 21: *cross tabulation between gender and effort expectancy*

Gender * Effort Expectancy Cross tabulation					
Gender		Disagree	Neutral	Agree	Total
Male	Count	3	12	122	137
	(%)	2.2%	8.1%	89.7%	100.0%
Female	Count	44	5	33	81
	(%)	54.4%	5.1%	40.5%	100.0%
Total	Count	46	17	154	217
	(%)	21.4%	7.0%	71.6%	100.0%

Source: *Research*

A high response rate of agree implies that the students feel that they require less effort while a low response of agree would imply that most students require more effort. Table 21 shows that 89.7% of all total males agree while 40.5% of the females agree, an indication that the when compared to the male, ***the female students feel that more effort is required to learn and acquire skills necessary for use of cloud computing services compared to the male students.***

The cross tabulation between duration of usage and effort expectancy in table 22 shows that 55.1% of the students who have used cloud services for a period of 1 year agree that their interaction with cloud computing services is clear and understandable, it is easy for them to be skillful at using cloud computing services and that it is easy to learn to operate and to use cloud computing services. On the other hand, 41% of those with duration of use of 1 years disagree, implying that they find that using cloud computing required a great deal of effort.

The percentage of those who disagree drops drastically with increase in experience as shown in table 22 where the percentage of disagree drops to 13.3% for those with experience of between 2-3 years and even further to 2.6% for those with experience of over 3 years, an indication that with growing experience, then the students find it easy to be skillful at using cloud computing services.

Table 22: *Cross tabulation between duration of use and effort expectancy*

Duration of Usage * Effort Expectancy Cross tabulation					
Duration of Use	**No. /(%)**	**Disagree**	**Neutral**	**Agree**	**Total**
1 year	No.	32	3	43	78
	(%)	41.0%	3.8%	55.1%	100.0%
2 to 3 years	No.	13	4	81	98
	(%)	13.3%	4.1%	82.7%	100.0%
Over 3 years	No.	1	8	30	39
	(%)	2.6%	20.5%	76.9%	100.0%
Total	No.	46	15	154	215
	(%)	21.4%	7.0%	71.6%	100.0%

Source: *Research*

In order gain an understanding of the relationship between age and the effort expectancy construct, a cross tabulation between age and effort expectancy was done; shown in table 23

Table 23: *cross tabulation between age and effort expectancy*

Age * Effort Expectancy Cross tabulation						
Age		Disagree	Neutral	Agree	Total	Aver: Young/Old
19 - 24	Count	15	10	89	114	**72.4%** of the Young Agree, While **20.6%** disagree
	(%)	13.2%	8.8%	78.1%	100.0%	
25-30	Count	18	4	32	54	
	(%)	33.3%	7.4%	59.3%	100.0%	
31-36	Count	8	0	23	31	
	(%)	25.8%	.0%	74.2%	100.0%	
37-42	Count	5	1	7	13	**62.5%** of the old agree while **31.3%** disagree
	(%)	38.5%	7.7%	53.8%	100.0%	
43+	Count	0	0	3	3	
	(%)	.0%	.0%	100.0 %	100.0%	
Total	Count	46	15	154	215	
	(%)	21.4%	7.0%	71.6%	100.0%	

Source: *Research*

The results in table 24 show a cross tabulation between gender and social influence. The results tend to suggest that more females (50.6%) disagree that social influence plays a role in their adoption and use of cloud computing services.

Table 24: *cross tabulation between gender and social influence*

Gender * Social Influence Cross tabulation						
			Disagree	Neutral	Agree	Total
Gender	Male	Count	43	42	52	137
		% within Gender	31.6%	30.1%	38.2%	100.0%
	Female	Count	40	20	21	81
		% within Gender	50.6%	24.1%	25.3%	100.0%
	Total	Count	83	62	72	217
		% within Gender	38.6%	27.9%	33.5%	100.0%

Source: *Research*

Table 25 shows a cross tabulation between age and social influence. The results show that for the young (age groups 19years to 36 years), 37% disagree, 30% gave the response of neutral while 33% gave the agree response. On the other hand, for the old (age above 36 years) 39% disagree, 44% gave the response of neutral while 16% responded with agree.

Table 25: *Cross tabulation between age and social influence*

Age * Social Influence Cross tabulation					
Age	Count/Percent	Disagree	Neutral	Agree	Total
19 -24	Count	43	29	41	**37%**(Disagree), **30%** (neutral) & **33%** (Agree)
	Percent (%)	38.1%	25.7%	36.2%	
25-30	Count	22	12	22	
	Percent (%)	39.3%	21.4%	39.3%	
31-36	Count	10	13	7	
	Percent (%)	33.3%	43.4%	23.3%	
37-42	Count	7	6	1	**39%** (disagree), **44%** (neutral) & **16%** (agree)
	Percent (%)	53.8%	38.5%	7.7%	
43+	Count	1	2	1	
	Percent (%)	25%	50%	25%	
Total	Count	83	62	72	217
	Percent (%)	38.6%	27.9%	33.5%	100.0%

Source: *Research*

Table 26: *Cross tabulation between duration of use and Social Influence*

Duration of Usage * Social Influence Cross tabulation					
Duration of Use	Count/Percent	Disagree	Neutral	Agree	Total
1 year	Count	44	20	16	80
	Percent (%)	55.7%	24.1%	20.3%	100.0%
2 to 3 years	Count	28	31	38	97
	Percent (%)	28.9%	32.0%	39.2%	100.0%
Over 3 years	Count	11	11	18	40
	Percent (%)	28.2%	25.6%	46.2%	100.0%
Total	Count	83	62	72	217
	Percent (%)	38.6%	27.9%	33.5%	100.0%

Source: *Research*

To understand the relationship between gender and facilitating conditions construct, a cross tabulation between gender and facilitating conditions was done; shown in table 27.

Table 27: *Cross tabulation between Gender and facilitation condition*

Gender * Facilitating Condition Cross tabulation						
			Disagree	Neutral	Agree	Total
Gender	Male	Count	18	41	77	136
		Percent (%)	13.2%	30.1%	56.6%	100.0%
	Female	Count	7	27	47	81
		Percent (%)	8.6%	33.3%	58.0%	100.0%
	Total	Count	25	68	124	217
		Percent (%)	11.5%	31.3%	57.1%	100.0%

Source: *Research*

Table 28 shows that 209 students, which is 96.5% of all students agree behavioral intention measure statements that; that they intend to continue using cloud computing services, they predict that they will continue using cloud computing services and will always use cloud computing services. 1.1% of the students disagree with these statements.

Table 28: *Cross tabulation of users and behavioral Intention*

No. of users * Behavioral Intention				
Response	Disagree	Neutral	Agree	Total
No. of Students	3	5	209	217
Percent	1.1%	2.4%	96.5%	100%

Source: *Research*

Table 29: *Tabulation between Age groups and Gender*

Age Group Vs Gender					
Age Groupings	**Male**		**Female**		**Total**
	Count	**Percent**	**Count**	**Percent**	**Count**
(19 -24) Years	83	73.5%	30	26.5%	113
(25-30) Years	28	50.9%	27	49.1%	55
(31-36) Years	18	56.3%	14	43.7%	32
(37-42) Years	5	38.5%	8	61.5%	13
43+ Years	2	50.0%	2	50.0%	4
Total	**136**		**81**		**217**

Source: *Research*

Table 30: *Duration of Use Vs Age Group*

Duration of Use Vs Age group			
	Category	**Male Count**	**Female Count**
1 year	Young (19 -36 years)	50	46
	Old (37 and above)	1	8
2 to 3 years	Young (19 -36 years)	45	21
	Old (37 and above)	4	1
Over 3 years	Young (19 -36 years)	34	5
	Old (37 and above)	2	0
	Total	**136**	**81**

Source: *Research*

4.5 Hypothesis Validation

H1: Performance expectancy is positively associated with the **behavioral intention** and this effect will be moderated by **gender** and **age**, such that the effect will be stronger for men and in particular younger men.

From table 10, the correlation between Performance Expectancy and Behavioral Intention is +0.315**, an indicator that Performance Expectancy is positively associated with Behavioral Intention. The significance (2-tailed) is 0.000, a value that is less than 0.05 which implies that this correlation is significant. When control variables are introduced, the correlation between performance expectancy and behavioral intention remains positive and significant; at +0.319 when gender is the control variable, at +0.311 when age is the control variable and at +0.318 when duration of usage is the control variable. When gender and age are used as control variables, the correlation still remains positive and significant with Pearson correlation coefficient of +0.315. The cross tabulation between gender and performance expectancy in table 19 shows that more male students agree with the measure statements of performance expectancy and furthermore, cross tabulation between age and performance expectancy shows that the agree response stronger in the young at 96% compared to the old at 93.5%. Given that most of the males are between ages of 19 years to 36 years, then the performance expectancy is stronger for males, especially the young. **Hypothesis 1 is supported** and we therefore accepted.

He and Lu (2007) in their research on factors that influence consumer' behavioral intention to accept and use mobile advertising established that *performance expectancy* and social influence were the main determinants of behavioral intention towards consumer's acceptances of mobile advertising, while facilitating condition and behavioral intention directly influenced use behavior. Using UTAUT, AlAwadhi and Morris (2008) investigated the adoption of e-government services in Kuwait and their findings showed that *performance expectancy*, effort expectancy and peer influence were the determinants behavioral intention to adopt and use e-government services while facilitating conditions and behavioral intention directly influenced the student's use behavior. Also, Tibenderana and Ogao (2008) found that *performance expectancy* and social influence were non-significant factors in predicting behavioral intention to use electronic Library services in Ugandan Universities. Further, Adell, E. (2009), while studying driver experience and acceptance of driver support systems established that *performance expectancy* and social influence had a significant effect on behavioral intention, while facilitating conditions directly influenced the use behavior. While examining the behavioral intention towards the adoption and use of Medical Teleconferencing Application, Biemans, Swaak, Hettinga & Schuurman (2005) found that *performance expectancy* and effort expectancy were the main determinants of behavioral intention while social influence did not play a significant role in determining behavioral intention towards acceptance ad use of the medical teleconferencing application.

H2: **Effort Expectancy** is negatively associated with **behavioral intention** and this effect will be moderated by **gender**, **age**, and **experience**, such that the effect will be stronger for females, particularly younger females, and particularly at early stages of experience.

The results in table 10 show that the correlation between Effort Expectancy and Behavioral Intention is -0.056479 (-ve) an indicator that Effort Expectancy is negatively associated with Behavioral Intention. Table 21 shows that more women (54.4%) were in disagreement with effort expectancy measure statements compared to those who agree (40.5%). Further, the results in table 29 shows that in this study, the number of women in the range 19 years to 36 years, who were categorized as young and with an experience of up to 1 year were 46, which is 56.8% of the total number of women sampled, an indicator that a higher percentage of the women disagree which the effort expectancy statements; 33 (71.7%) disagree, while

13(28.3.2%) agree with the Effort Expectancy measure statements. There were 21 young female students with experience of between 2 years to 3 years, and out of these, 8 (38.1%) disagree with the EE measure statements, while 13 (61.9%) agree. These results show that with growing experience, young female find that they need to use less effort. However, the correlation between EE and BI in this study was found to be weak and not significant; Significance (2-tailed) is more than 0.05 which implies that this correlation is not significant. **Hypothesis 2 is therefore not supported** and hence we discard the hypothesis.

Rahman et al., (2011) found that the Intention to Use Digital Library among Malaysian Postgraduate students was mainly determined by Performance Expectancy and *Effort Expectancy* in addition to information quality and service quality. Yahya et al (2011) using UTAUT model researched on measuring user acceptance of E-Syariah portal in syariah courts in Malaysia and found that performance expectancy, *effort expectancy* and social influence appeared to be significant direct determinants of user acceptance and usage behavior. Adell, E. (2009) established that *effort expectancy* did not have an effect on behavioral intention, unlike in most cases of information technology adoptions. While examining the behavioral intention towards the adoption and use of Medical Teleconferencing Application, Biemans, Swaak, Hettinga & Schuurman (2005) found that performance expectancy and *effort expectancy* were the main determinants of behavioral intention while social influence did not play a significant role in determining behavioral intention towards acceptance ad use of the medical teleconferencing application.

H3: Social Influence is positively associated with behavioral intention and this effect will be moderated by **gender**, **age** and **experience**, such that the effect will be stronger for women, particularly older women in the early stages of initial usage.

From the results in table 10, the correlation between Social Influence and Behavioral Intention is -0.007 (-ve) an indicator that Social Influence is negatively associated with Behavioral Intention. The results in table 24 show that overall, 50.6% of the female students were in disagreement with the social influence measure statements compared to the males at 31.6%. Out of the 40 (50.6%) women who agree, 33 (82.5%) were young (ages; 19 – 36) while the remaining 7 (17.5%) were old. These results show that social influence has a negative association with behavioral intention and that the effect is stronger for younger women contrary to the stated hypothesis. The significance (2-tailed) is more than 0.05 which implies that this correlation is not significant. These findings imply that **Hypothesis 3 is not supported** and we therefore reject it.

Tibenderana and Ogao (2008) in their research on factors influencing behavioral intention to use electronic Library services in Ugandan Universities found that performance expectancy and *social influence* were non-significant factors. Jong, D and Wang, T (2009) studied the student acceptance of web-based learning system and the research results showed that performance expectancy, facilitating conditions and *social influence* have significant influence on behavior intention and additionally, behavior intention and *social influence* have direct impact on system usage. Adell, E. (2009), while studying driver experience and acceptance of driver support systems established that performance expectancy and *social influence* had a significant effect on behavioral intention, while facilitating conditions directly influenced the use behavior. While examining the behavioral intention towards the adoption and use of Medical Teleconferencing Application, Biemans, Swaak, Hettinga & Schuurman (2005) found that performance expectancy and effort expectancy were the main determinants of behavioral intention while *social influence* did not play a significant role in determining behavioral intention towards acceptance ad use of the medical teleconferencing application.

H4: **Facilitating conditions** will not have any significant influence on **behavioral intention.**

The partial Correlation coefficient results for the correlation between facilitating conditions and behavioral Intention in table 10 is positive at 0.227** and the correlation is significant. When control variables are introduced, table 13 shows that the Pearson correlation coefficient is +0.228, +0.223 and +0.225, when gender, age and duration of use respectively, are introduced individually. Furthermore, table 16 shows that when the three moderators are together introduced as control variables, the correlation is still significant with a Pearson correlation coefficient of +0.224. **Hypothesis 4 is not supported** and we therefore reject it. This result invalidates the findings of Venkatesh et al (2003) which showed that facilitating conditions construct does not have any significant effect on behavioral intention.

Adell, E. (2009), while studying driver experience and acceptance of driver support systems established that performance expectancy and social influence had a significant effect on behavioral intention, while *facilitating conditions* directly influenced the use behavior. Adell,

E. (2009) further established that effort expectancy did not have an effect on behavioral intention, unlike in most cases of information technology adoptions. He and Lu (2007) in their research on factors that influence consumer' behavioral intention to accept and use mobile advertising established that performance expectancy and social influence were the main determinants of behavioral intention towards consumer's acceptances of mobile advertising, while *facilitating condition* and behavioral intention directly influenced use behavior. AlAwadhi and Morris (2008) investigated the adoption of e-government services in Kuwait and their findings showed that performance expectancy, effort expectancy and peer influence were the determinants of behavioral intention to adopt and use e-government services while *facilitating conditions* and behavioral intention directly influenced the student's use behavior. In an attempt to establish the role played by motivation in e-learning technology adoption, Maldonado, Khan, Moon and Rho (2009) found that *facilitating conditions* did not play a significant role in predicting the use behavior.

H5: **Behavioral Intention** will have a significant influence on **use behavior**

The results of the study show that the independent variables PE, EE, SI and FC have an influence on BI. All students who agree with the measure statements for behavioral intention are using the cloud computing services, then we argue that the high percentage (96.5%) of agree in table 28 explains the fact that the students are currently using the services and intend to do so in future. **Hypothesis 5 is supported** and we therefore accept it. These findings are consisted with the findings in the reviewed literature; Behavioral Intention directly influences the use behavior.

He and Lu (2007) in their research on factors that influence consumer' behavioral intention to accept and use mobile advertising established that performance expectancy and social influence were the main determinants of behavioral intention towards consumer's acceptances of mobile advertising, while facilitating condition and *behavioral intention* directly influenced use behavior. AlAwadhi and Morris (2008) investigated the adoption of e-government services in Kuwait and their findings showed that performance expectancy, effort expectancy and peer influence were the determinants of behavioral intention to adopt and use e-government services while facilitating conditions and *behavioral intention* directly influenced the student's use behavior.

4.6 Summary of the findings:

Hypothesis Code	Dependent Variable	Independent Variable	Moderators	Explanation
H1	BI	PE	Gender & Age	PE positively associated with BI and the effect is stronger for me; particularly the young. The correlation is significant.
H2	BI	EE	Gender, Age & Duration of use	EE is negatively associated with BI and the effect is stronger for young females in their initial stages of adoption. The correlation is not significant.
H2	BI	SI	Gender, Age & Duration of use	SI is negatively associated with BI and the effect is stronger for younger women. The correlation is not significant.
H4	BI	FC	Gender, Age & Duration of use	FC has a significant effect BI. This effect is moderated by Gender, Age and Duration of usage.
H5	Use Behavior	BI	None	The BI has a significant influence on the behavioral intention

4.7 The Focus Group Discussion

The study used focus group discussion (FDG) in order to discuss and explore the students responses to various construct measures, in an effort to explain possible underlying reasons for various responses. We established that the whenever students found that a cloud service useful to them, they were sufficiently motivated to learn how to use it and did not therefore consider the effort required to learn and gain skills on how to use it as a hindrance to the adoption and use of the cloud service. Further, some of the students that participated in the FGD revealed that they learnt how to use cloud services voluntarily, over a long period of time, out of fun and not because of an urgent pressing need to use the cloud service for an important task. Another contributing factor as one of the participant put it; "*Given that most cloud services providers include a help guide on their website, in addition to availability of numerous sites on the internet with clear and straight forward how to do procedures, I did not have to exert much effort to learn how to use the services*". Therefore, whereas the association between EE and BI had an inverse relation, therefore confirming Venkatesh et al., (2003) findings in part, the correlation between the two was not significant.

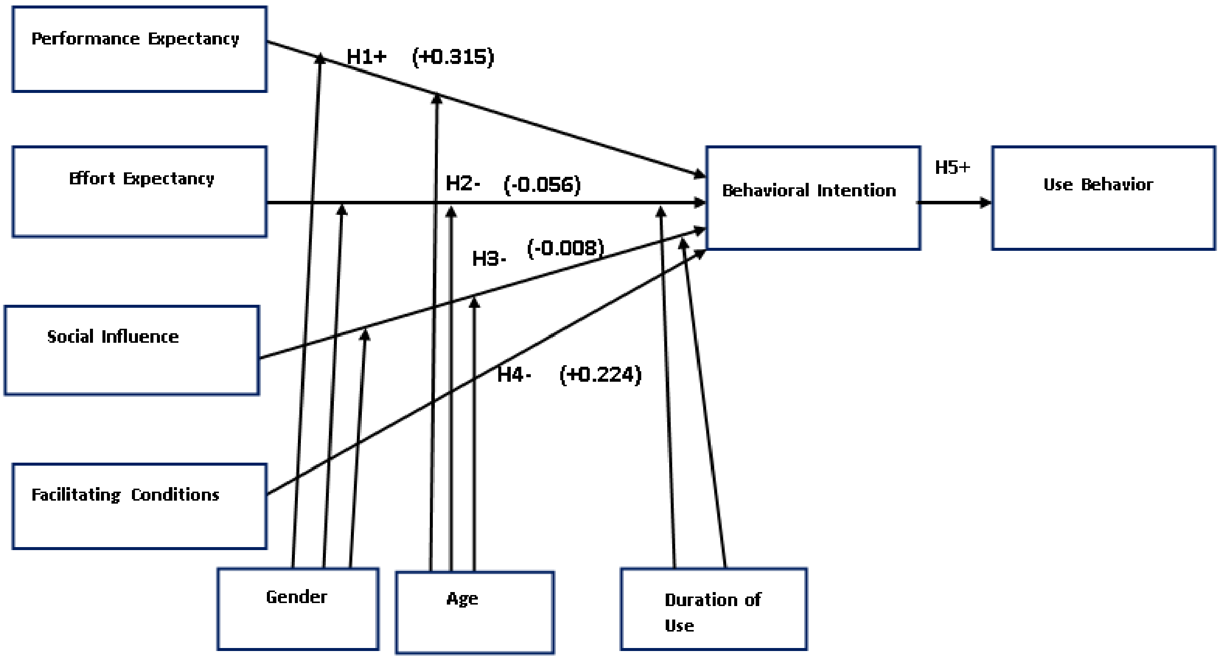
Social influence, otherwise referred to as Subjective Norm is as an individual's perception of social normative pressures from friends, colleagues, bosses, parents or teachers beliefs that he or she should or should not perform a particular behavior. Venkatesh et al., (2003) found that in an environment where the technology adoption is not mandated, the social influence construct would not have any significant influence on behavioral intention. This study involved university students who adopted publicly available cloud computing services on voluntary basis. Through the Focus Group Discussion, the student revealed that they were reluctant to admit that they learnt how to use or were influenced to use the cloud services by others. The ego factor could not allow the students to readily admit because of the fear that their colleagues would look down upon them. The female students were more willing to admit that they were socially influenced to learn and use cloud services than their male counterparts.

The focus group discussion established that whereas students were eager to learn and know how to use cloud services, they paid attention to those that significantly contributed towards making their work easier or those that helped them accomplish their task much faster. As one participant summed it up "*it would not hurt to learn all that there is to learn about available cloud services and how to use them, but I tend to pay close attention to those cloud services that appear to help me in my daily tasks*"

4.8 The conceptual model showing casual relationships and Correlation coefficient values

The figure below shows the research conceptual model used in this research with the casual relationship between the variables and the partial correlation coefficient values.

Figure 16: *Conceptual Model - casual relationships and Correlation coefficient values*



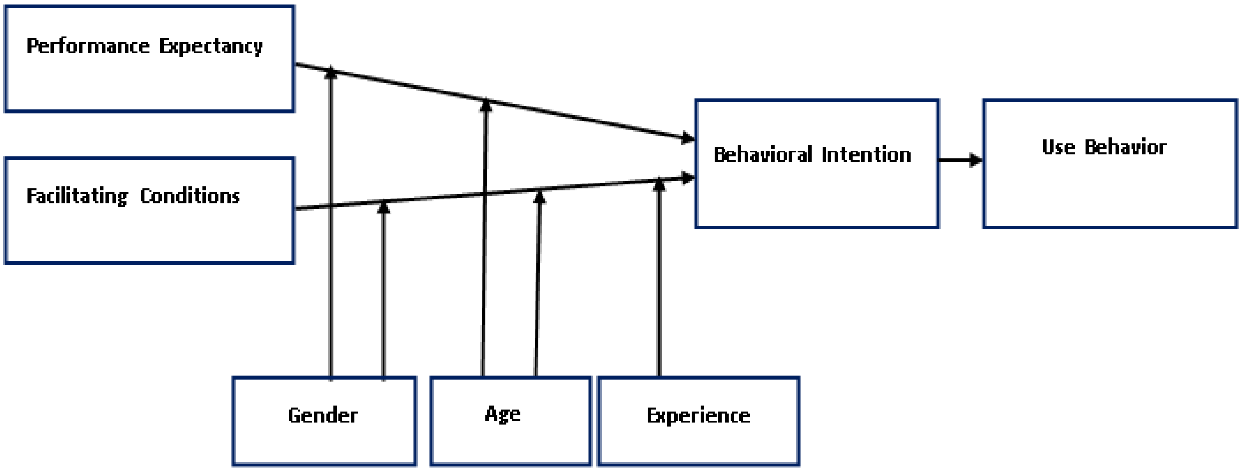
Source: *Research*

4.8 The Resulting Model

The Pearson correlation coefficient results in table 17 and table 18 shows that only two independent variables; Performance Expectancy and Facilitating Conditions have a significant effect on the Behavioral Intention. Table 28 shows results of cross tabulation between the number of users and the behavioral intention measure statements. The percentage of users who agree with the measure statements is 96.5%, while those in disagreement were 1.1%. The higher percentage of the students who agree to these statements explains why they are currently using the cloud services. The behavioral intention was found to directly influence Use Behavior.

The resulting modified model, which can be used as a post adoption evaluation model is shown figure 17.

Figure 17: *Resulting Model*



Source: *Research*

CHAPTER 5 : CONCLUSION AND RECOMMENDATIONS

5.0 Conclusion

The finding of this study show that in the Kenyan University setting, social influence and effort expectancy are negatively associated with behavioral intention but their association with behavioral intention is not significant and therefore they do not have any significant influence on behavioral intention to accept and use cloud computing services among the Kenyan university students. The performance expectancy and facilitating conditions are both positively associated with behavioral intention towards acceptance and use of cloud computing services and that the two are main determinants of behavioral intention to accept and use cloud computing services in the Universities in Kenya. The study established that; there is minimal assistance available to the students towards use of cloud computing services in the Universities in Kenya, the female students and especially younger ones feel that more effort is required to learn and acquire skills necessary for use of cloud computing services compared to the male students and, with growing experience, the students find it easier to learn and become skillful at using cloud computing services.

5.1 Research objectives:

First objective: *Establish and compare the levels of utilization of Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS).*

The research question associated with this research objective was; which category of computing service; PaaS, SaaS and IaaS is most utilized? We sought to establish and compare the levels of utilization of the different forms of services offered by cloud computing, with the ultimate aim of finding out how they rank in terms of usage. The results in table 3, shows that Software as a Service (SaaS) is the most utilized cloud service, followed by Infrastructure as a Service while Platform as a Service is the least utilized among the three categories of cloud services. This is an indicator that the objective was realized.

Second objective: *Establish factors that influence the acceptance and usage of cloud computing services in institutions of higher learning in Kenya.*

To address this objective, we sought answers to the second research question of the study; what factors influence the acceptance and usage of cloud computing services in institutions of higher learning in Kenya? The results in tables 10, 11, 12, 13, 14, 15, 16, 17 and 18 show that Performance Expectancy (PE) and Facilitating Condition (FC) have significant influence on behavioral intention, while Effort Expectancy and Social Influence do not have significant effect on behavioral intention. The research findings of Davis (1989), while developing Technology Adoption Model established that perceived usefulness, a construct which just like performance expectancy measures the degree to which an individual believes that using a system or new technology will help him or her to attain gains in job or task, was a significant factor that influences technology adoption. In their research and while testing the UTAUT model in four different organizational settings for a period of six months Venkatesh et al., (2003) established that among the three primary constructs that influence adoption and use of technology namely Performance Expectancy, Effort Expectancy and Social Influence, performance expectancy was the most important in influencing technology adoption and use. Their findings showed that PE had a direct and significant effect on behavioral intention.

The findings of this study on the Performance Expectancy construct concur with the findings of Venkatesh et al., (2003). This is a further confirmation that performance expectancy is an important factor in adoption and use of technology and this can be extended to cloud computing services adoption in institutions of higher learning in Kenya. He study results show that Performance Expectancy was found to associate positively and had significant effect on behavioral intention.

In contrast to Venkatesh et al., (2003) findings on Facilitating Condition, which stated that FC does not have significant influences use behavior, this study found that Facilitating Condition significantly influence behavioral intention, moderated by age, gender and duration of use. The correlation results in tables: 10, 14, 16, 17, 18 and appendix 3 show that the association between Facilitating condition and Behavioral intention is positive and significant. The use behavior was found to be directly influenced by behavioral intention. Table 28 shows a cross tabulation between the number of users and the behavioral intention summary of responses. The percentage of the users who agree with statements is 96.5%, which translates to 209 students against the actual 217 who are using the services. The results show that the objective was achieved; we were able to identify the factors that influence behavioral intention and also proved that behavioral intention directly influences use behavior.

Venkatesh et al., (2003) and Davis (1989) found that effort expectancy (perceived ease of use) of new technology was negatively associated with adoption of technology and that this construct was significant in influencing adoption and use of technology. This study found that in the adoption and use of cloud computing services in universities in Kenya, the effort expectancy or perceived ease of use was negatively associated with behavioral intention, but the correlation between EE and BI was found to be weak and therefore EE did not have significant effect BI.

Third objective: *Determine the moderators to the factors that influence acceptance and usage of cloud computing services in the institutions of higher learning in Kenya.*

To address this objective, there was a need to provide answers to the third research question; what is the effect of the moderating factors of age, gender and experience on the primary determinants? Venkatesh et al., (2003) established that the association between Performance expectancy is positively associated with the behavioral intention and this effect will is moderated by gender and age, such that the effect will be stronger for men and in particularly for younger men. This means therefore that men and especially the younger ones are keen to adopt cloud computing services whenever they perceive that that new technology will improve their performance. The results are in agreement with the findings Venkatesh et al., (2003), by showing that the association between PE and BI is moderated by age and gender. The result of cross tabulation between age and performance expectancy in table 20, shows that there more students below the age of 36 who agree that cloud computing services are convenient, useful and contribute positively towards accomplishment of tasks. The combined responses shows that 96% of all the young (ages: 19 years - 36 years) agree with the performance expectancy statements compared to 93.5% of the old (Ages above 36 years), which implies that the performance expectancy is stronger towards the young. Out of the 96% of the young who agree, 64.5% are male while the remaining 35.5% are female, a strong indication that the performance expectancy is strong towards the young male students.

The second factor that was found to influence behavioral intention was facilitating conditions. Venkatesh et al., (2003) found that FC directly influence use behavior and does not have a significant influence of behavioral intention. This study established that FC has a significant effect on BI and the association is moderated by gender, age and duration of use. The effect was found to be moderate for both males and females. The third objective was realized.

Fourth Objective: *Present a model for post adoption evaluation of cloud computing services utilization in the institution of higher learning in Kenya*

This objective involved answering the question; what is the appropriate model for post adoption evaluation of cloud computing services in the institution of higher learning? The results of the study from tables 10 to 18 show that the association between the independent variables (PE and FC) and dependent variable (BI) are significant, while the association between independent variables (EE & SI) and dependent variable (BI) is not significant. Further, using the aggregate of the responses of the behavioral intention statements and to estimate the number of student who agree that they will or are likely to continue using cloud services in future, we argue that the high percentage agree responses, as shown on table 9 and figure 15, explains the current usage of cloud services by the students. This leads to the conclusion that, behavioral intention directly influences use behavior. By considering the correlations that are significant between the independent (PE & FC) and dependent variable (BI) and the association BI and use behavior as explained above, the resulting new model that can be used for post adoption evaluation of cloud services is shown in figure 17. The fourth objective of the study was therefore realized.

5.2 Research Assessment:

Whetten, D.A. (1989) developed a framework for evaluating or assessing a conceptual paper. The framework outlines the factors that should be considered in judging a conceptual paper in order to assess its value added contribution. This factors can be summarized as; clarity of expression, impact on research, timeliness and relevance. The framework outlines seven key questions that must be answered in order to measure whether or not a study has made significant contributions to the subject area. The final output of this study is therefore evaluated against the framework.

a) What is new? Does the research make a significant, value-added contribution to the current thinking?

These questions aim at establishing the significant added value contribution of the study to the existing body of knowledge, in the subject area. The study had four objectives that we sought to address. First, to find out the cloud services utilization levels, secondly to identify the primary determinants of cloud computing services adoption and use in the institutions of higher learning in Kenya, thirdly to identify the likely moderating factors in the association between the primary determinants and cloud computing adoption and finally, based on the identified primary determinants and the moderating factors in the second and third objectives respectively, to come up with a model that can be used for post adoption evaluation of cloud computing services in the institutions of higher learning in Kenya. The study established that Effort Expectancy does not have significant influence on behavioral intention. These findings present contrasting results to those by Davis (1989) and Venkatesh et al., (2003) who argued that Effort Expectancy or ease of use, was a significant determinant of technology adoption. The findings also seem to invalidate the findings of Venkatesh et al., (2003) with regard to the facilitating condition construct. Venkatesh et al., (2003) argued that Facilitating condition did not have a significant effect on behavioral intention instead; it directly influenced the technology usage. The findings on the two constructs; Effort Expectancy and Facilitating Condition brings a new dimension to technology adoption that differs from the findings of Davis (1989) and Venkatesh et al., (2003).

b) So what? How will the research change cloud services adoption?

The findings of the study show that in the universities in Kenya, where cloud computing adoption and use is not mandated, performance expectancy and facilitating condition are the two primary determinants of behavioral intention, which in turn directly influences use behavior. The findings of this study will greatly inform cloud computing adoption because the cloud computing service vendors and providers will take advantage of these findings to focusing on availing services that target specific user needs and in addition, to provide conditions or enabling infrastructures that will facilitate the adoption and use of cloud computing services. By producing cloud services that target users with a certain specific need, users will tend to only explore and adopt cloud services that help them accomplish certain tasks.

c) Are the underlying logic and supportive evidence compelling?

The study has its foundation on concrete theories and models established and proven by previously studies. The identification of the independent variables in the conceptual model for this study was based on UTAUT model, which consolidated eight previous technology adoption models/theories and therefore includes aspects of adoption that are lacking in other previous models. The formulation of the hypothesis was based on three aspects; solid theoretical foundation of previously conducted and proven study findings, our own intuition, general knowledge and observations. A good example is the fact that even though Venkatesh et al., (2003) established that in an environment where adoption of technology is not mandatory, social influence would not have a significant effect on behavioral intention. We went ahead to test whether lecturer influence and peer influence would lead to SI having a significant effect on behavioral intention in an environment where adoption was voluntary. Secondly, whereas Venkatesh et al., (2003) argued FC directly influences Use behavior and that FC does not have significant influence of behavioral intention, with the background knowledge of the state of internet access and associated limitations in the Kenyan Universities, we sought to establish whether there was a facilitating condition construct would have direct and significant influence on the behavioral intention.

d) How thorough was the study

We first established that studies on individual adoption of cloud computing services had not been previously carried out in Kenya. This was achieved through a thorough and detailed review of literature related to technology adoption, which later narrowed down to adoption of cloud computing technology for individual users, with a case study of Kenyan Universities. In order to ensure that the sample size used in the study was representative of the population of study, the sample was derived as a function of the population, using the formula derived by Yamane (1967:886) and in line with Mugenda and Mugenda, (2003) who argued that; in the situations where time and resources allow, a research should take as big a sample as possible since this would measure the reliability of the results. Furthermore, we took into consideration Kothari (2004) who emphasized that an optimum sample is one which fulfills the requirements of efficiency, representativeness, reliability and flexibility. The guide for the study was a conceptual model derived from literature with strong and solid justification. The selection, design and development of the data collection instruments was based on several factor; the conceptual model, carefully analysis of the pros and the cons of the various options of data collection instruments available and a thorough review of the data collection methods and instruments used in previous studies. The reliability of the data collection instrument was established in order to ensure that the collected data was reliable. This was achieved through pre-testing of the questionnaire and the FDG guides among a selected group of prospective students for semantics and syntax, seeking expert opinion and guidance on the same and computing the Cronbach's Alpha coefficient, which measures the degree of consistency between multiple measures of a variable. Data was collected from bonafide students of the targeted universities and analyzed using SPSS, a tool that has been used successfully in other previous prominent technology adoption studies.

e) Is the thesis well written? Does it flow logically?

The structure of the study is such that it starts out by giving an informative background review on cloud computing and technology adoption. It reviews technology adoption and the theories and models that have been used to explain technology adoption. The study then identifies the UTAUT model from which it derives the conceptual model, with justifications given for the choice of the UTAUT model. A clear research methodology is outlined; it explains research design, the data collection instrument and justifies the choice. Furthermore, we explain how the reliability and validity of the instrument was achieved. Data collection, cleaning process and analysis process is clearly outlined. The results are analyzed by extracting the general characteristics, summary of responses statistics, correlation analysis and cross tabulation of important variables and their moderators. The discussion of the results is strictly based on the study analysis output and in order to put the results into perspective in relation to other studies, there is a purposeful comparison of various aspects of this study's findings with other previous studies from time to time. Conclusions are drawn, limitations highlighted and recommendations made. There is therefore a logical flow in the project write-up.

f) Why now? Is it of interest to the people?

The adoption and use of computers and computing technology is aimed at saving costs, reducing amounts of time required to accomplish complex computational tasks, ensuring accuracy, increasing production speeds and precision and automating highly repetitive tasks. There has been a steady increase in the need for computing and computing services in the various fields and this presents several challenges chief among them; the cost of acquiring and owning of the resources required to meet and satisfy their computing needs and in addition where the situations demand, the requirement to develop and deploy applications, the need to lay a complex data communication network infrastructure, carry out routine maintenance, periodic upgrades of hardware components, setting up, configuring and periodic upgrades to the system and application software components. Cloud Computing, therefore presents a paradigm shift in computing (Luis et al., 2008). The shift represents a move away from personal computers and enterprise server systems (e.g. application servers and file servers) that may prove costly to implement, to a "cloud" of computers. Since cloud computing presents an option of being able to use computing services without having to incur the cost acquiring computers, laying down of complex infrastructure and additional costs of maintenance, the study is of interest to users, companies who would be interested in using cloud services to run their operations, cloud service providers and vendors and government agencies that may be concerned with formulating legislations relating to cloud computing.

g) Who else including academic researchers are interested in this research?

The technology adoption researchers, technology for development researchers and individual user perception researchers will be interested in the study, with the ultimate aim of establishing why cloud computing services adoption may differ from other technology adoption. Cloud computing services providers/vendors and prospective cloud services investors will be interested in this study in order to find what influences individual adoption of cloud services and out how they can satisfy their customers' needs by providing cloud services that address specific needs as well as provide facilitating conditions for use of cloud computing services.

5.3 Limitations and recommendations for further work

There are two major limitations to this study that have implication for further research work. The resulting model was derived from the data obtained from the students who were already using cloud services. The study did not introduce cloud computing services to the student in order to learn the adopter's behavior before, during and after adoption of the cloud computing services. Given the time constraints in this study, it would be important for future research work to observe the adoption process and behavior change of the students before, during and after adoption. This would allow for the validation of the new model.

Random sampling may not have allowed us to collect fair samples as relates to factors such as age, gender and duration of use which may have profound moderation effects on the model relationships. It is therefore recommended that future research should adopt or use purposeful sampling in order to gain proper representation of students in terms of age, gender and duration of use.

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Appendix 1: Research Questionnaire

The questionnaire has four main sections; the first section is a brief and general overview of the background and the objectives of the study. The second section is designed to capture individual characteristics that included; the Name of the responded, age, gender, level of study and the institution where the responded studies. The third section of the questionnaire aims at establishing whether the user had any experience of using the cloud services, the types of services used and duration of time the responded had used the services. The fourth section is a series of statements on each construct where a responded is required to use a 5 point likert scale to indicate their level of agreement with various statements about the constructs in question.

Background:

This questionnaire is part of a research that seeks to establish factors about "adoption and use of cloud computing services in the institutions of higher learning in Kenya. What is cloud computing? This is an Information Technology paradigm where services are hosted and accessed from the "**cloud**". A cloud consists of an Information Technology infrastructure (servers, data centers, applications and platforms) that located on the internet. This infrastructure is owned and managed by a vendor or service provider e.g. Google. As opposed to traditional computing where data and services are accessed from desktops, laptops or enterprise server systems, in cloud computing services are accessed from the cloud, which is hosted on the internet. The user does not need to know the physical location of cloud infrastructure or deployment and configuration details; they can access and use the services available in the cloud from anywhere as long as the user has a connection to the internet and they meet the conditions set by the vendor.

Privacy and Confidentiality statement:

Your privacy and confidentiality is guaranteed as you participate in this study. The information you give in this questionnaire will be treated as privacy and confidentiality and will ONLY be used for the purposes for which is collected.

SECTION A: STUDENT INFORMATION

1. **Name of student** (Optional)____

2. **Current Level of Study**: Postgraduate ☐ Undergraduate ☐

3. **Age** ____________

4. **Gender**: Male ☐ Female ☐

5. **Institution (Name):** University of Nairobi (**UoN**) ☐ Strathmore University (**SU**) ☐

   Catholic University of East Africa (**CUEA**) ☐ Kenya Polytechnic University College (**KPUC**) ☐

SECTION B: CLOUD SERVICES

1. Have you used any cloud computing service: (**Email**, **Google Docs**, **YouTube**, **Sendspace**, **Dropbox**, **Sky Drive**, **Google Apps Engine,** **Ubuntu-one** or **Windows Azure**)

   Yes ☐ No ☐

   If yes, kindly state which one (s): ____

2. When did you start using the service? (**Month and Year**) _____________

3. How often do you use the service(s)?

   ☐ Daily ☐ Weekly ☐ Monthly ☐ Yearly ☐ Do not Know

SECTION C:

Please indicate your level of agreement with the following statements by ticking the appropriate box:

Key: Disagree (**D**); Disagree Somewhat (**DS**); Neutral (**N**); Agree Somewhat (**AS**); Agree (**A**)

1. **PERFORMANCE EXPECTANCY (PE)**

No.	Statement	D	DS	N	AS	A
PE1	I find cloud computing service(s) useful in my tasks.					
PE2	Using cloud computing service(s) enable me to accomplish tasks more quickly					
PE3	Using cloud computing service(s) increases my productivity.					
PE4	Using cloud computing service(s) is convenient to me					

2. **EFFORT EXPECTANCY (EE)**

No.	Statement	D	DS	N	AS	A
EE1	My interaction with cloud computing service(s) is clear and understandable					
EE2	It is easy for me to become skillful at using cloud computing service(s).					
EE3	I find cloud computing service(s) easy to use.					
EE4	Learning to operate cloud computing service(s) is easy for me					

3. **SOCIAL INFLUENCE (SI)**

No.	Statement	D	DS	N	AS	A
SI1	People who influence my behavior think that I should use cloud computing service(s)					
SI2	People who are important to me think that I should use cloud computing service(s).					
SI3	My lectures have encouraged me to use of cloud computing service(s).					
SI4	My peers have encouraged me to use of cloud computing service(s).					

4. FACILITATING CONDITIONS (FC)

No.	Statement	D	DS	N	AS	A
FC1	I have the resources (**financial and/or equipment**) necessary to use cloud computing service(s)					
FC2	I have the knowledge necessary to use cloud computing service(s).					
FC3	Cloud computing service(s) is not compatible with the university systems I use.					
FC4	There are people available for assistance with cloud computing service(s) difficulties.					

5. BEHAVIORAL INTENTION (BI)

No.	Statement	D	DS	N	AS	A
BI-1	I intend to continue using cloud computing services					
BI-2	I predict I would continue to use cloud computing services.					
BI-3	I will always use cloud computing services.					

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Your participation in this study is highly appreciated.

Thank you.

Appendix 2: Cronbach's alpha reliability test Output

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Alpha if Item Deleted
PE1	75.5193	43.4732	.2268	.1572	.7929
PE2	75.8508	40.1387	.4040	.4432	.7740
PE3	75.8453	41.5204	.2752	.3571	.7848
PE4	75.6740	41.5209	.3916	.3579	.7804
EE1	75.8785	40.5074	.3865	.3577	.7262
EE2	75.8619	40.5641	.3877	.4254	.7764
EE3	75.8232	40.2241	.4525	.5573	.7723
EE4	75.8287	41.2316	.3258	.4433	.7815
SI1	76.6851	35.4058	.5252	.5731	.7498
SI2	76.8895	35.1322	.5598	.6265	.7452
SI3	77.1050	38.1834	.1720	.2960	.8124
SI4	76.2873	38.3614	.3994	.2790	.7894
FC1	76.4751	39.5174	.2460	.3870	.7879
FC2	76.0608	41.4130	.2109	.2131	.6894
FC3	78.6133	43.1607	.0387	.1759	.7300
FC4	77.0166	40.2719	.1336	.2028	.7071
BI1	75.5746	42.2680	.4025	.3576	.7842
BI2	75.6409	42.1759	.2394	.3234	.7880
BI3	75.8232	40.9352	.3526	.2939	.7793

Cronbach's Alpha reliability test results summary

CONSTRUCT	VALUE
• Performance Expectancy	0.7830
• Effort Expectancy	0.7641
• Social Influence	0.7742
• Facilitating Condition	0.7286
• Behavioral Intention	0.7905

Alpha value of > 0.7 is considered acceptable level of reliability (Santos, 1999).

Appendix 3: Correlations Summary

Summary of Correlation				
Independent/Dependent Variables	**Moderating Factors**	**Correlation Coefficient**	**Sig. (2 tailed)**	**Interpretation**
PE & BI	None	0.315**	0.000	Significant
	Gender	0.319**	0.000	Significant
	Age	0.311**	0.000	Significant
	Duration of Use	0.318**	0.000	Significant
	Gender & Age	0.315**	0.000	Significant
	Gender, Age & Duration of use	0.315**	0.000	Significant
EE & BI	None	-0.044	0.525	Not Significant
	Gender	-0.065	0.342	Not Significant
	Age	-0.033	0.626	Not Significant
	Duration of Use	-0.054	0.428	Not Significant
	Gender & Age	-0.054	0.437	Not Significant
	Gender, Age & Duration of use	-0.056	0.416	Not Significant
SI & BI	None	-0.007	0.92	Not Significant
	Gender	-0.01	0.885	Not Significant
	Age	-0.001	0.984	Not Significant
	Duration of Use	-0.014	0.838	Not Significant
	Gender & Age	-0.005	0.947	Not Significant
	Gender, Age & Duration of use	-0.008	0.906	Not Significant
FC & BI	None	0.227**	0.001	Significant
	Gender	0.228**	0.001	Significant
	Age	0.223**	0.001	Significant
	Duration of Use	0.225**	0.001	Significant
	Gender & Age	0.302**	0.001	Significant
	Gender, Age & Duration of use	0.224**	0.001	Significant

Appendix 4: Focus Group Discussion Guide

“Post Adoption Evaluation model for Cloud computing services utilization in Institutions of Higher Learning in Kenya”:

Focus Group Discussion Guide

Preparation

Consent forms will be distributed to all users prior to the FGD sessions. The consent form is reproduced here for completeness.

Consent form

Thank you for agreeing to participate in this research. We are very interested to hear your valuable opinion on factors that influence the adoption and use of publicly available cloud computing services among university students in Kenya.

- *The purpose of this research is to establish the factors that influence the adoption and use of cloud computing services among university students in Kenya. Our aim is to identify the determinants of cloud computing adoption and use and the moderating factors.*

- *The information you will give us is highly confidential and your name will not be associated with anything you say in the focus group or any other time during the research process*

- *We will be tape recording the focus group discussions so that we can make sure we capture all your thoughts, opinions, ideas and suggestions from the group. Once again no names will be attached to the tapes and the recordings will be erased once we transcribe the information*

- *You do not have to answer any question if you do not feel like doing so and you may withdraw from the focus discussion group study at any time*

- *As part of the research we will also be asking you some questions individually. If you are not sure about a question please feel free to ask any one of us or you can contact the lead researcher through telephone number below this form*

Thank you, Muhambe Titus Mukisa

(Tel 0720 048 445)

Introduction –10 Minutes

Welcome

Will introduce myself and my two research assistants at the same time sending out a sign in sheet with few demographic questions such as age, gender, and experience in using cloud computing services (Duration of use)

- *Ask the group members to say their names*
- *Describe briefly who we are and what we do*
- *Inform the participants why we are carrying out the research and what we will do with the information we collect*
- *Explain to them why they are participating in the FGD*

Explanation of the process

- *Find out how many have participated in an FGD before*
- *Explain what FGD is about*
- *Clarify that we are interested in gathering information not achieving consensus*
- *Looking for priorities not long winded lists*
- *Explain that we will also use questionnaires*

Logistics and Ground Rules

The FGD will last at most one hour

- *Feel free to move around*
- *Ask them to suggest some ground rules such as*
- *Everyone should participate*
- *Turn off cell phones*
- *Stay with the group*
- *Ask if anyone has a question before beginning*

***Turn on the tape recorder remembering to give people time to answer questions before moving in with probes.

FGD Guide – 60 to 70 Minutes

We would like the discussion to be informal, so there's no need to wait for us to call on you to respond. In fact, we encourage you to respond directly to the comments other people make. If you don't understand a question, please let us know. We are here to ask questions, listen, and make sure everyone has a chance to share

Let us start by finding out from you whether you have used cloud computing services: At this point we will explain what cloud computing is and give examples of services by mention a list

Demonstration of the use of SaaS (Google Docs), PaaS (Windows Azure) and IaaS (Send Space) (15 Minutes)

What are you general comments about cloud computing services? Do you find them useful?

Probes for discussion

- *Do you use cloud services? Why?*
- *When did you start using cloud computing services?*
- *What prompted you to start using them?*
- *Were you influenced to start using cloud computing services? By who?*
- *What is your opinion on the computing environment at the university? Does it is allow you to access your favorite cloud services? If no, why?*
- *What features are available in cloud services?*
- *What additional functionality and features would you like to see in cloud services? Why?*
- *What features do you find most useful?*

What is interesting thing about using cloud computing services?

Probes for discussion

- *What is the most interesting thing about using cloud services?*
- *How did you learn about it?*
- *How many cloud services do you use? Why do you use each?*
- *What has been your experience with subsequent cloud services i.e. after the first?*
- *In a scale of 1 – 10 how much effort did you exert in order to learn how to use them (Why do you think it took that much effort?)*

Have you ever encountered difficulty when attempting to use a cloud service? What did you want to do and could not be able to do?

Probes for discussion

- *Why were you not able to do it?*
- *Did you feel frustrated not being able to use the cloud service?*
- *Was there someone ready to help?*
- *Did the help make you able to accomplish the task? (Depends on previous probe)*

Do you feel limited when attempting to use cloud computing services?
What university factors could limit the use of cloud computing services?
Put probes, e.g. no Internet access in the universities, other people are not using the cloud services; there is no one to consult in case of problems, etc.

Probes for discussion

- *Do you use cloud computing service outside the university environment?*
- *How often do you use cloud computing services?*
- *Would you pay to use cloud computing services? How much?*
- *Based on your experience with using cloud services, will you continue using the cloud services in future? Why?*

That concludes our FGD. Thank you very much for coming and sharing your thoughts and opinions with us. If there is additional information that you think of later on please feel free to contact us and we shall get in touch with you.

Thank you very much.

Muhambe Titus Mukisa

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Appendix 5: Letters of Introduction/Recommendation for research