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Cloud Computing Adoption in Afghanistan: A Quantitative Study Based on the Technology Acceptance Model

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Walden University
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Abstract

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BS, Saint Joseph University, 1988

Doctoral Study Submitted in Partial Fulfillment

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Abstract

Cloud computing emerged as an alternative to traditional in-house data centers that businesses can leverage to increase the operation agility and employees' productivity. IT solution architects are tasked with presenting to IT managers some analysis reflecting cloud computing adoption critical barriers and challenges. This quantitative correlational study established an enhanced technology acceptance model (TAM) with four external variables: perceived security (PeS), perceived privacy (PeP), perceived connectedness (PeN), and perceived complexity (PeC) as antecedents of perceived usefulness (PU) and perceived ease of use (PEoU) in a cloud computing context. Data collected from 125 participants, who responded to the invitation through an online survey focusing on Afghanistan's main cities Kabul, Mazar, and Herat. The analysis showed that PEoU was a predictor of the behavioral intention of cloud computing adoption, which is consistent with the TAM; PEoU with an R^2 = .15 had a stronger influence than PU with an R^2 = .023 on cloud computing behavior intention of adoption and use. PeN, PeS, and PeP significantly influenced the behavioral intentions of IT architects to adopt and use the technology. This study showed that PeC was not a significant barrier to cloud computing adoption in Afghanistan. By adopting cloud services, employees can have access to various tools that can help increase business productivity and contribute to improving the work environment. Cloud services, as an alternative solution to home data centers, can help businesses reduce power consumption and consecutively decrease in carbon dioxide emissions due to less power demand.

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Dedication

I want to dedicate this study to my family, especially my wife, for her patience she had shown during the past two years that I have committed to achieving my goal.

Acknowledgments

Many people were engaged, supporting me during the mission to finalize my DIT and deserve my written appreciation for completing with success of my doctoral program. First of all, I need to acknowledge my Chair of study and mentor, Dr. Bob Duhainy for his close guidance with constant serenity, and his insights that drove me up from the start at a weak point of knowhow, where I was, to the completion of this degree. Next, I wanted to address my gratitude to the contribution of my second member committee, Dr. Gary Griffith, who helped a lot in advancing my work through the approval phases of the process. Moreover, I want to acknowledge the URR and program director Dr. Steve Case for his close support and help in laying the foundation for the research. Then, I say a special thank you to my wife, Mireille, who supported me in my dedicated time and efforts to succeed in my objective. A special thanks to my daughter Carine who all times kept encouraging her father to make it happen. Finally, I thank my young son of 12 years old, Alex, for his mature understanding and support throughout the program and always. I would also like to thank my professional colleagues, and others who assisted me in one way or the other, especially those who contributed to facilitating the data collection. And first of all, I give God Almighty the glory for helping me through.

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Section 1: Foundation of the Study

I examined in this doctoral study, external factors that influence information technology (IT) solution architects' behavioral intentions of adoption of cloud computing services (CCS) in Afghanistan. I used the quantitative correlational method to analyze the intentions of IT solution architects in Afghanistan to use cloud computing services once they are made available. The study would allow revealing findings determined and evaluated by the independent variables of the study, which are PeS, PeP, PeN, and PeC. The outcomes and findings of this study can help IT architects as well as IT leaders and decision-makers to decide whether future IT solutions include cloud computing services. The new technology of cloud computing is considered a low-cost IT solution and easy access to software for small and medium-sized businesses (SMEs). The SMEs, with CCS, may gain a better work environment that enhances customer service experience, fast on-demand products, and services deployment using a cost-efficient IT infrastructure.

Background of the Problem

After the industrial revolution, manufacturers were the ones creating market demand. The computer networking revolution and the internet innovation promoted consumer requirements, customers' expectations, and increasingly fierce competition that reshaped business strategies to develop attractive products and better service offerings (Sorek, 2016), hence market demand became a consumer-driven industry. Therefore, the quality of service and high customer expectations are external pressures that influence IT leaders to seek better products and faster time to market, relying on advanced technologies (Ye, Cao, Wang, Yu, & Qiao, 2016). Advanced technologies would allow IT leaders to accommodate disruptive innovations that are the differentiating factor helping them to succeed in ventures (Ross & Blumenstein, 2015). Chief Information Officers (CIO) and IT leaders seek ways and means to reduce costs, provide high-quality services, and increase customer satisfaction. Tools, applications, and infrastructure challenge IT leaders in that the more technology advances, the more charges are incurred (Hamari, Sjöklint, & Ukkonen, 2016). Therefore, IT leaders need a groundbreaking that leverage new techniques and tools such as IT service management platforms, process automation, resource virtualization, and cloud computing (Ross & Blumenstein, 2015).

The virtualization of desktops, computing powers, network storages such as "Network Attached Storage" (NAS), molded the foundation of IT shared resources and services that evolved a structured infrastructure termed nowadays as the cloud computing (Jeong, Yi, & Park, 2016). CCS allowed IT leaders to change the old computer systems to the virtual computing ecosystem. The virtual computing molded IT thinking to go beyond cost and budget management, where IT leaders are privileged to manipulate technical capacities to promote business through service innovation and attractive product portfolios used as driving-forces for an unbeatable competitive advantage (Jeong, Yi, & Park, 2016). CCS provides IT leaders with the capacity to run IT with a significant reduction in capital and operation expenditure comparing to a housed data center, with a better quality of service, faster system scalability, and higher service availability (Ye et al., 2016).

Problem Statement

Cloud computing emerged as a key IT solution to businesses. However, CCS adoption was a challenge to cloud providers as well as to their customers (Sabi, Uzoka, Langmia, & Njeh, 2016). 77% of organizations' CIOs adopted at least one type of cloud service; however, 56% of them perceived the complexity of their IT infrastructure as the most significant barrier to large scale adoption (Phaphoom, Wang, Samuel, Helmer, & Abrahamsson, 2015). The general IT problem is that most small and medium businesses in developing countries fail to adopt CCS. The specific IT problem is that some IT managers lack information regarding the relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, PEoU with the intent to adopt CCS.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with the intent to adopt CCS. The target population was the technology IT solution architects of SMEs in Afghanistan. The independent variables were PeS, PeP, PeN, PeC, PU, and PEoU, and the dependent variable was the intent to adopt and use CCS. The study's findings could contribute to positive social change by providing a reduction in energy consumption and carbon dioxide emissions, once CCS adoption spreads out in developing countries.

Nature of the Study

The methodology of the study was quantitative and involved in deductive reasoning. The quantitative method allows scholars to generalize findings from a specific sample to a broader population (Borrego, Douglas, & Amelink, 2013; Counsell & Harlow, 2017). I used the quantitative method to generalize the findings of my study in Afghanistan to a broader population in similar neighboring countries. Leydens, Moskal, and Pavelich (2013) and Lewis (2015) said that a qualitative study involves an interpretive methodology to analyze new problems and explore new theories and a detailed collect data from interviews, documents, and other sources and investigate and analyze contextual information regarding the study phenomena. Hence, the qualitative method was not appropriate for my study as the contextual information would be ineffective in understanding what the larger population is about concerning CCS. As well it would not allow generalizing the findings to a broader population.

Similarly, the mixed method is a methodology for conducting research that encompasses collection, dissection, analysis, and integration of both quantitative and qualitative data in the same study (Cendán et al., 2017). Because I was not using qualitative data, the mixed methodology was unsuitable. I selected the quantitative over the qualitative design because I wanted through statistical analysis to analyze the cloud computing adoption phenomenon by identifying the relationships among the variables of interest, sampling the population of the industry, and generalizing the findings of the study in terms of the country of Afghanistan as well as the neighboring countries.

I considered using a correlational or nonexperimental design. I used a predictive correlational design to assess whether there was a relationship between the variables of the study. For the experimental design, predictive variables cannot be controllably manipulated for treatment to deduce any cause-effect analysis upon the dependent variable; therefore, a real experimental design was not applicable. The empirical quasi-experimental design was as well not suitable in this study as it required, as explained by Bellemare, Masaki, and Pepinsky (2017) as well as Becker et al. (2017), a cause and impact variables measurement of a manipulative test on a target population without random assignment.

In this research, I wanted to increase the predictive power between the variables based on the proposed interrelationship model of the enhanced TAM (ETAM) theoretical framework of the study. The predictive correlational methodology and design helped me to predict variances involving variables and was the right design for this study. In conclusion, the experimental and quasi-experimental designs do not comply with the correlational predictive method of the theoretical framework application I wanted for this study.

Research Question

RQ: Is there a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with the intent to adopt CCS?

Hypotheses

Null Hypothesis

H_0: There is no relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

Alternative Hypothesis

H_a: There is a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

Theoretical Framework

I grounded this study in the technology adoption model (TAM) theory as the theoretical framework for this study. The TAM theory is used to measure users' attitudes and reasons behind technology adoption (Valtonen et al., 2015). Fred Davis developed TAM's theory in 1989 due to a gap in instrumentations to predict users' acceptance of computers when he was working as a professor assistant at the University of Michigan (Davis, 1989). Davis's original TAM model contained only two variables, termed as PU and PEoU, that Davis found to be predictors of SME employees' computer adoption and use (see Figure 1).

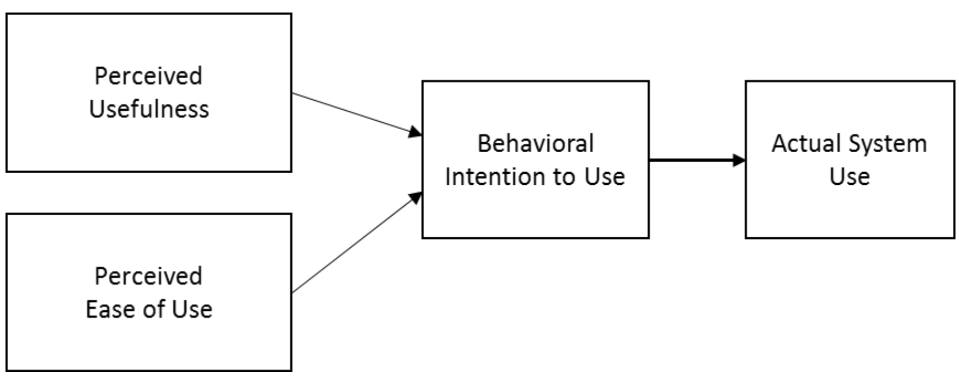


Figure 1. TAM framework structure. Reprinted from *Davis et al. (1989, p.985)*

In 2000, Davis and Venkatesh extended the original TAM to develop a new model referred to as the TAM2 by integrating two processes, which are the social influence process and the cognitive instrumental process. The social influence process included three constructs, which are subjective norms, voluntariness, and image. In contrast, the cognitive instrumental process included three other constructs that are job relevance, output quality, and result demonstrability (see Figure 2).

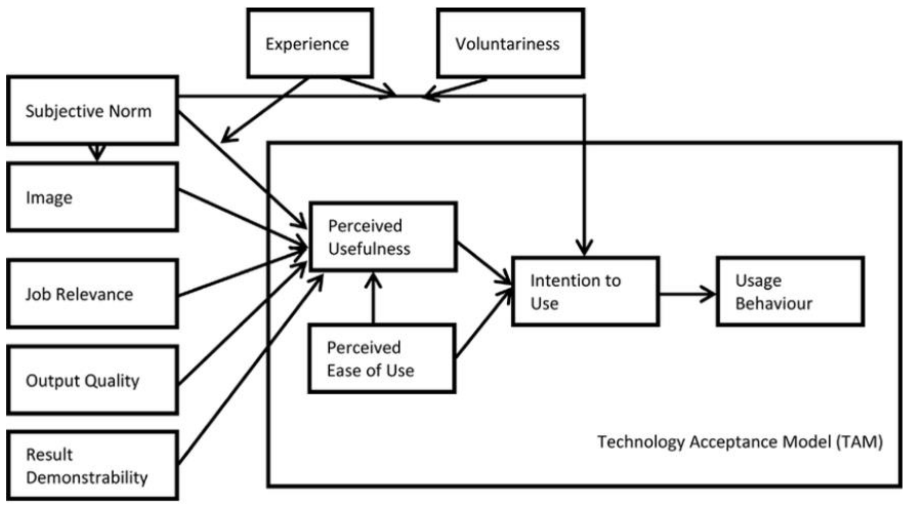


Figure 2: Constructs of TAM2. Reprinted from *Davis et al. (2000)*

Despite the latest developments in IT and smart handheld devices, the TAM is still effectively used as a theoretical framework for many IT studies. The findings of research analysis based on TAM in the IT industry showed that TAM is a useful tool in measuring IT consumers' attitudes to technology acceptance (Wann-Yih & Ching-Ching, 2015). Mortenson and Vidgen (2016), demonstrated that TAM is an overall useful tool to predict user acceptance of new technology such as cloud computing, as well as evaluating competing for cloud services and products. Therefore, the TAM could be used in this study to measure cloud computing technology adoption in Afghanistan.

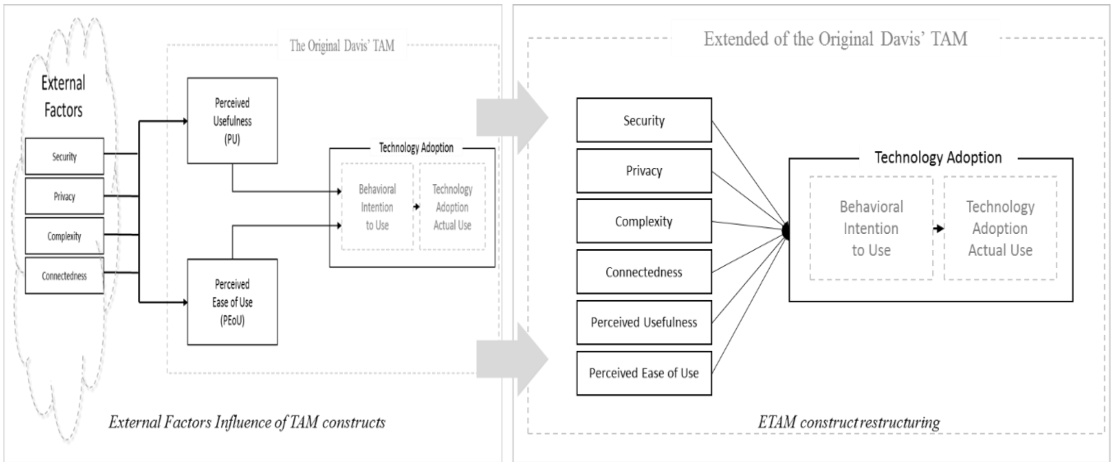


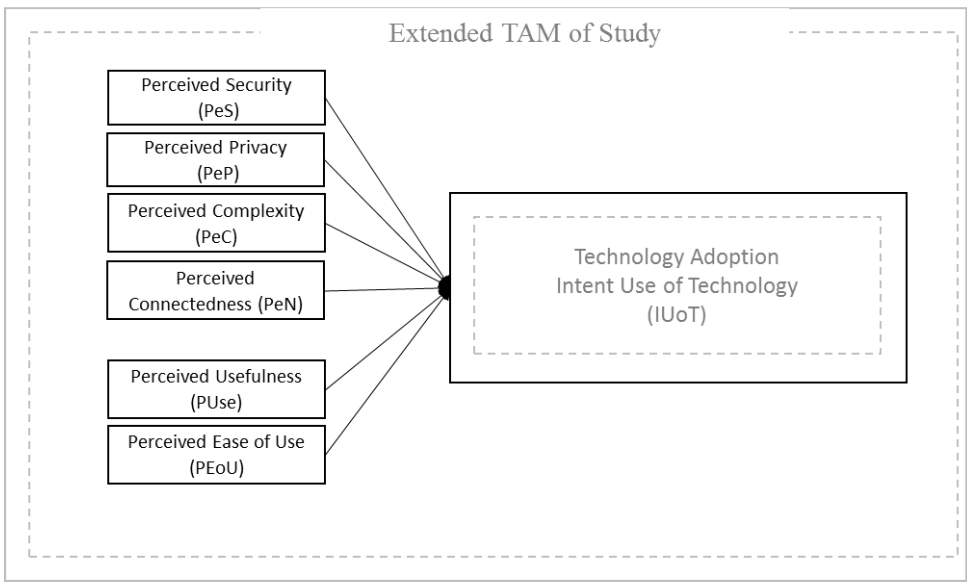
Figure 3. Evolution of the constructs ETAM of the study

Wixom and Todd (2005) as well as Abdullah, Ward, and Ahmed (2016) stated that TAM model advantage is the flexibility to add independent variables of choice to the framework to analyze some external factors and understand how and why they influence the adoption decision of some users of technology. The users of technology in our case are IT solution architects, the population of the study that is using and offering CCS. Figure 3 illustrates how the external factors or independent variables PeS, PeP, PeN, and PeC, as well as the core constructs of TAM, PU and PEoU, contributed to IT solution architects to influence IT decision-makers to adopt and use CCS.

Security, trust, social influence, and reliability are four external variables that impact technology adoption and can be added to core TAM constructs to measure users' security and reliability perceptions of a particular technology. Dutot (2015), based on his study findings of technology adoption of mobile communication technology, said PeS, perceived reliability, and perceived trust, which are factors that influence technology user believes that a secure and reliable system would enhance his or her job performance without any extra effort, are key TAM constructs to examine technology adoption for mobile users.

Figure 3bis. Constructs of the ETAM of the study.

The ETAM model of this study, see Figure 3bis, illustrates the inter-relationships framework structure of the constructs PeS. PeP, PeN, PeC, PU, and PEoU that I will



analyze to determine the influence of interactions between those variables of prediction with the dependent variable intention of adoption and use of technology (IUoT). Therefore, I conducted a multiple regression analysis to examine the relationship of PeS, PeP, Pen, and PeC with PU and PEoU and these latter with IUoT. My ETAM model was applicable because it allows testing a theoretical framework, which is the ETAM of the study. The ETAM of the study is an acceptance model of CCS technology, allowing to measure the influence of the external factors PeS, PeP, PeN, and PeC of IT solution architects on the constructs PU, PEoU, and IUoT of TAM. SME leaders adopt technology that enhances performance and reduces operational expenses. Abdullah, Ward, and Ahmed (2016), Changchit and Chuchuen (2016), and Dutot (2015) used TAM to analyze external variables such as connection quality, complexity, security, and privacy and measure impacts on the behavioral intention of adoption of technology on SMEs' IT leaders. However, the ETAM of my study can provide me with enough measurable constructs PeS, PeP, PeN, PeC, PU, PEoU, and IUoT to determine the relationships between the variables.

Definition of Terms

The following definitions provide context for key terms:

Bare-metal hardware: A bare-metal hardware is a computer server in a metallic box that is a single-tenant physical server (Chang et al., 2016).

Cloud service provider (CSP): A CSP is an IT or internet service provider (ISP) running Internet-based IT service and sells using pay-per-use or a subscription. Amazon, Google, IBM, and Microsoft are service providers referred to as first movers into CCS (Tang & Liu, 2015).

Hybrid Cloud: A hybrid cloud means the deployment of a data center technology through which CCS in a mixed configuration of the private and public cloud. With a hybrid cloud, computing resources are in the public cloud, but customer data can be installed in a community or private cloud setting (Chang, Kuo, & Ramachandran, 2016).

IaaS: Infrastructure-as-a-Service (IaaS) is a standardized and automated service offering of computing resources supplemented by storage and networking resources that are owned and hosted by a CSP and offered on-demand to customers. Customers can provision their own computing power units (CPU) and storage capacity to create their virtual data center (VDC) infrastructure. CCS Customers use a web-based graphical user interface that serves as an IT operation management tool to manage the VDC environment (Huang, Ganjali, Kim, Oh, & Lie, 2015).

IT Solution Architect. A solution Architect is a person who leads to introduce a technical vision and ecosystem architecture of a specific IT solution to IT managers and leaders. IT solution architects can be employed by big companies. For SMEs a third-party IT service provider can provide consulting services to propose IT solutions as a service (Waterman, 2018). An IT solution architect includes IT senior managers, IT senior administrators, IT senior engineers, and IT professional freelance consultants.

PaaS: Platform-as-a-service (PaaS) is represented as a diagram between the SaaS and the IaaS layers. PaaS is a CCS model in which a CSP provides hardware and software tools. PaaS is usually used for application development and related testing scenarios (Madduri et al., 2015).

Private Cloud: The private cloud is a CCS model in which the owner or company possesses the data center, physical machines, and storage as well as data and applications running on them (Chang et al., 2016).

Public Cloud: The public cloud is a CCS model of cloud computing deployment technology in which the CSP owns the data center and computing infrastructures, and other companies access them for a pay-as-you-go fee (Chang et al., 2016).

Server virtualization: Server virtualization is an IT technology that allows creation of a virtual server (VM). A VM is a software-based server conceptually similar to a physical server. a physical server can run one or many VMs. A VM has its own resources of CPU, Memory, and hard drive (Chang et al., 2016).

SaaS: Software-as-a-Service (SaaS) is a CCS model that allows CSP to provide access to software solutions to SME through the internet. SaaS CCS are software solutions like customer registration management, accounting and finance, Human resource, and procurement. CCS allows the SMEs' employees to connect and login as if the software is running on personal computers (Safari, Safari, & Hasanzadeh, 2015).

Assumptions, Limitations, and Delimitations

Assumptions

An assumption is a statement alleged to be true without tangible proof to support it. In other words, assumptions are researcher beliefs that are considered valid within the research but are challenging to attest (Staffel, 2016). Berner and Flage (2016) stated that researcher beliefs drive approaches and the research process as well as conclusions drawn afterward. The key assumption in research study was that IT solution architects and experts in Afghanistan are aware of the IT infrastructure problems and understand the need to enhance the existing IT service platform such as connectivity and security to increase the quality of IT services. However, Afghan IT solution architects, who are the population of this study, may not be familiar with CCS technology and related pros and cons. Self-reporting bias is an issue. I assumed that through consent form communications, providing participants with anonymity and freedom as well as requesting honest and unbiased answers would provide the participants with the comfort that helps to mitigate this issue. Moreover, in this study, I assumed as well that the respondents had deep knowledge about the services they adopted or denied adopting as well as survey questions, and that they would truthfully and accurately answer them.

Limitations

Limitations defined as the weaknesses of the study design that may impact interpretations of the research (Reio Jr., 2016). Busse, Kach, and Wagner (2016) and (Chatterji, Findley, Jensen, Meier, & Nielson, 2016) said that limitations in experimental studies are perceived inadequacies that may reduce the validity and reproducibility of study findings. A limitation may be respondents' inaccurate feedback due to misinterpretation or misunderstanding of a question so that respondents might select a wrong answer. A limitation may be due to the sample frame bias, as Curran (2016) and Becker et al. (2017) said, where because of the random selection of participants, the responses bias may appear when respondents provide information different from those who did not participate in taking the survey.

Delimitations

Delimitations are boundaries a researcher creates in his/her study (Sampson et al., 2014). Delimitations restrict specific approaches in the research, and the researcher is the one who defines them (Klein, 2016). Nilsson (2017) said that delimitations are self-imposed boundaries of the researcher based on the perceived reality of limited resources and capacities. Nilsson (2017) confirmed that once those delimitations exceeded, they may cause challenges that could compromise the results and conclusions of a study.

The study was based on a limited population of registered SMEs where the participants' population selection criteria included being an IT solution architect in Afghanistan currently employed by an ICT working SME with at least 5 years of experience, fluent in English, and CCS aware. These criteria provided a specific population of participants since there were around 400 ICT SME registered at MOCI in Afghanistan, most of them in the capital city of Kabul at the time of the study.

By providing an analysis of the assumptions, limitations, and delimitations, I was able to designate the scope and boundaries of the study. The analysis of the assumptions allowed me to provide some mitigation procedures that would reduce potential bias in the study.

Significance of the Study

Contributions to IT Practice

This study may be valuable to IT leaders and senior managers as it enriches their understanding of the right strategies regarding the adoption of CCS as well as operational efficiency and management performance. Ge et al. (2017) and Kaleem, Jain, and Husain (2017) said cloud computing is contributing to SMEs' cost savings. CCS is an alternative solution to the in-house data center and enhancing SMEs' digital product development and shorter time-to-market through the CCS flexible delivery and fast scalability of service. This study culminates in the exploration of the determinants of cloud adoption using the TAM by measuring the impact of PU and PEoU in connection with the influence of PeS, PeP, PeN, and PeC on IUoT.

Padilla, Milton, Johnson, and Nyadzayo (2017) said marketers tend to believe that a faster time-to-market of digital products can be realized by CCS being providers of a scalable PaaS and customizable SaaS with the right desired quality of service. Such ratification of business leaders might lead organizations and SMEs to adopt CCS that can be used as an unbeatable competitive advantage. CCS could help SMEs' IT leaders to restructure their IT departments and find new ways to support IT infrastructure to offer high performing digital services and products with better quality. As such, CCS might help to increase the performance of SMEs and may encourage business leaders to address new strategies and open new markets relying on CCS as stable setup models (Garrison, Wakefield, & Kim, 2015). Padilla, Milton, Johnson, and Nyadzayo (2017) said CCS transforms businesses into agile corporations, creates an improved work environment and increase employee confidence and productivity, increase customer satisfaction because of the digital services quality and consequently support business brand reputation and equity.

Implications for Social Change

This study may stimulate positive change as CCS provides easy access to global scholar research and studies and encourages diverse streams of online education and ease an individual's intellectual development. CCS increases organizations' performance by enhancing the work environment and improving employee's productivity (Paul, Aithal, &

Bhuimali, 2017; Padilla, Milton, Johnson, & Nyadzayo, 2017). CCS facilitates global social interactions and develop groups inter-communication through the internet and social media platforms (Bajaber et al., 2016). CCS could contribute to operational expenses reduction that would conveniently result in lowering products' prices (Checko et al., 2015).

Moreover, cloud virtualization and capacity management of resource efficiency would allow more computing power with less bare-metal servers, which would drastically reduce IT waste and the nonrecyclable components deposited to landfills (Ge et al., 2017). CCS adoption could reduce the number of in-house data centers and therefore reduces electrical power and cooling consumption, which would radically reduce carbon dioxide gas emissions and support green technology (Kaleem, Jain, & Husain, 2017). An appropriate strategy for CCS adoption may help the IT leaders to succeed in creating a cost-effective operational improvement that might increase profit margins as well as the overall welfare of SMEs' employees.

A Review of the Professional and Academic Literature

In my review of the literature, I used the following online libraries: Google Scholar, Walden Library, ProQuest Central, ACM Digital Library, and Science Direct. The search keywords were: *cloud computing*, *Middle East*, *Afghanistan*, *cloud computing survey*, *TAM*, and *cloud computing adoption*. The search parameters were generally limited to peer-reviewed scholarly works published since 2015. However, older articles related to the TAM theory and other significant studies on cloud computing architecture and theories were included. Some subtopics involved in the literature, such as cloud computing business benefits, cloud services models, cloud architectural types, the Internet as infrastructure, an evolution of TAM, and theoretical framework presentation. I verified the peer-reviewed status of journal articles by using Ulrich's Global Serials Directory, and by analyzing the journal websites to reach 90% of peer-reviewed materials. In this study, the number of articles published within 5 years of my projected graduation date was 92%.

My study should reveal IT problems that prevent solution architects and IT managers of SMEs in Afghanistan to implement CCS solutions for their enterprise business. My review of the literature has two essential components, which are cloud adoption related to decision-making and TAM. Therefore, to deliver suitable structured information of these two components, I presented cloud industry benefits and business adoption decision-making categories as follows: (a) the purpose of the study, (b) the IT problem of lack of adoption by SMEs, (c) introducing the cloud computing industry structure, (d) listing the cloud benefits and features as a solution, (e) explaining the TAM and other similar theories starting from the initial cognitive works of the theory, (f) introducing and explaining the literature ETAM framework, and finally, (g) addressing the cloud adoption challenges.

Application to the Applied IT Problem

Purpose of the Study

In this quantitative correlational study, I wanted to estimate the relationship between the PeS, PeP, PeN, PeC, PU, and PEoU with the intent to adopt CCS of the IT architects of SMEs in Afghanistan. The target population of the study was the technology IT solution architects of the SMEs in Afghanistan. The independent variables of the study were PeS, PeP, PeN, PeC, PU, and PEoU, and the dependent variable was IUoT. Several previous academic studies about cloud computing adoption demonstrated the various benefits of CCS for SMEs in the developing countries (Al-Ruithe, Benkhelifa, & Hameed, 2017; Ross & Blumenstein, 2015). The literature of the study was conducted to focus on the various benefits of the cloud computing architecture of the SMEs after adoption, with similarity focus to several previous studies such as de Bruin and Floridi (2017), Ross and Blumenstein (2015), as well as Wann-Yih and Ching-Ching (2015). The research analysis was conducted to elaborate on the main challenges that IT architects were facing and preventing them from adopting cloud computing, with similarity focus to several previous studies such as Stergiou, Psannis, Kim, and Gupta (2018). The research data collection was based on an online survey questionnaire to measure the predictors' causal effect on the intention of the adoption of CCS. The study findings may help IT architects and leaders in developing countries to re-structure a better IT strategy based on in-depth environmental, organizational, and technological dynamics analysis. Moreover, the research findings may contribute to positive social change by participating in reducing energy consumption and carbon dioxide emission (Kaur & Chana, 2015) once CCS adoption spreads out in developing countries.

IT Problem - Cloud Computing Adoption by SMEs

Cloud computing services were still relatively new and misunderstood, and hence causing the adoption rate to rise slow (Shiau & Chau, 2016). Despite the significant benefits that CCS could offer to business operation, some SMEs deserted the idea due to critical factors such as incomplete compliance to conditions from Service Level Agreements (SLA), standards application, or processes re-engineering (Rani, B. K., Rani, B. P., & Babu, 2015). Rinderle-Ma, Ly, Göser, and Dada (2012) said that organizations had adopted cloud services and fined due to lack of compliance with anti-money laundering directives, as the cloud service provided was not grafted with the right security setup. Schulte, Janiesch, Venugopal, Weber, and Hoenisch (2015), in their study findings of cloud adoption rate improvement, emphasized that business process compliance has been described as a vital risk by executives and analysts in various business sectors. Therefore, cloud providers should comply with the business process model through cloud standards and make the right adjustment while reaching SLA. Rani et al. (2015) said cloud computing promises to enhance scalability, flexibility, and cost-efficiency. However, in practice, there remain many suspicions about the use of cloud computing resources in the enterprise applications and e-commerce context. Al-Ruithe et al. (2017) \stated while cloud computing had become a matured technology in developed countries, it was still treated as a new tech-archetype in some countries, especially in developing nations. They exemplified the Kingdom of Saudi Arabia (KSA), a country that stands at an early stage of considering the technology, and that it only had few cases of adoption. Al-Ruithe et al. (2017) confirmed that cloud computing was still an emerging technology in the KSA, and hence, a fact that can be generalized to other developing countries of the Middle-East that were similar to KSA in nature and culture such as Afghanistan. It is worth mentioning that the majority of governmental and public sector institutions in KSA do not discuss cloud adoption, where only 30 % of public sector organizations are willing to adopt cloud services, while only 29 % adopted some of the available cloud computing services. Raza, Adenola, Nafarieh, and Robertson (2015), stated in their study about the slow growth of cloud computing services over the years, that social environment changes and technology emergence helped to enhance cloud computing growth. Still, the achieved rate was much less than the expectations at the beginning of the era of CCS.

Dubai Technology Entrepreneur Center (DTEC), with the support of the Dubai Silicon Oasis Authority (DSOA) and IBM, reported that IaaS and PaaS Cloud services developed at a steady pace in the Middle-East (DTEC, 2017). The report represented the cloud infrastructure market of both services as being projected to grow at a compound annual growth rate (CAGR) of 26.4% from USD 2.31 billion in 2016 to USD 7.46 billion by 2021. In contrary to these expectations, the report extended an in-depth study for Dubai with a focus on business startups to find that only 24 % built their IT systems for business operations on the cloud (DTEC, 2017). However, DTEC (2017) reported other countries of the Middle-East still have much to learn about the state of cloud adoption for the startup and existing SME communities.

Afghanistan is a country that suffered wars and insecurity for several decades. The scholar and academic analysis and studies are scarce if nonexistent. Messmer (2010), in her article concerning USA Army contribution to technology development in Afghanistan, confirmed that the USA military took cloud computing into the rugged country, by packing the hardware and software technology into mobile boxes to aid warfighters in the sky and on the ground. According to Messmer's article, it is the Defense Information Systems Agency (DISA) that made the use of private cloud computing in the United States for the benefit of the military in Afghanistan. Therefore, and according to Messmer (2010), 2010 was the first time the military ran cloud computing in remote areas of Afghanistan to help warfighters in the field to enhance surveillance and decision-making information.

The ministry of telecommunication and information technology of Afghanistan (MCIT) published some articles concerning specific technological advancements and infrastructure development in the country (MCIT, 2016). MCIT (2016) said 23 million people possessed mobile phones, 6 million were users of 3G/4G wireless internet services, and the yearly spending on telecommunication and IT exceeded 2.4 billion USD. MCIT objectives are to supply highspeed internet all over the country, avail internet, enhance mobile banking, deploy a digital platform for the national identity card (NID), and introduce the concept of eGovernment to digitize and automate most government's services. Technology has dramatically transformed communications and governance in Afghanistan. There remains a long way to gain a stable technological infrastructure such as fiberoptic network, wireless data coverage of quality, highspeed internet with high availability architecture, and uninterrupted services.

Review of the Theoretical Framework

In this study, I used TAM as the core basis of an Extended TAM (ETAM) design to identify reasons why cloud computing, as a technology, was not intensively been adopted in the country of the study. I relied on the main aspects of the ETAM to provide a flow of explanations of how and why the cloud computing services may or may not be accepted (Davis, Bagozzi, & Warshaw, 1989; Dutot, 2015; Sharma, Al-Badi, Govindaluri, & Al-Kharusi, 2016). The ETAM that I explored in this study would theoretically be capable of identifying whether the IT managers in Afghanistan would adopt and utilize the technology based on the PEoU and the PU. According to Davis (1989) The PU is defined as the level of feeling the user has about the technology whether it enhances his/her job performance or not, and the PEoU is defined as the belief of the user whether the technology would take minimal effort to get the tasks done (Davis, 1989; Koufaris, 2002). Lu, Liu, Yu, and Yao (2014) revealed that users of technology appraise their behavior base on their desirability of the PU. Persico, Manca, and Pozzi (2014), as well as many prior researchers, showed that PU is used as one of the indicators to prove the acceptance of technology (Sharma et al., 2016). Hence, the objective of my quantitative correlational study was to examine, based on TAM as a core framework, the parameters and factors that inspire the decision-making of cloud computing adoption by IT solution architects of SMEs in Afghanistan.

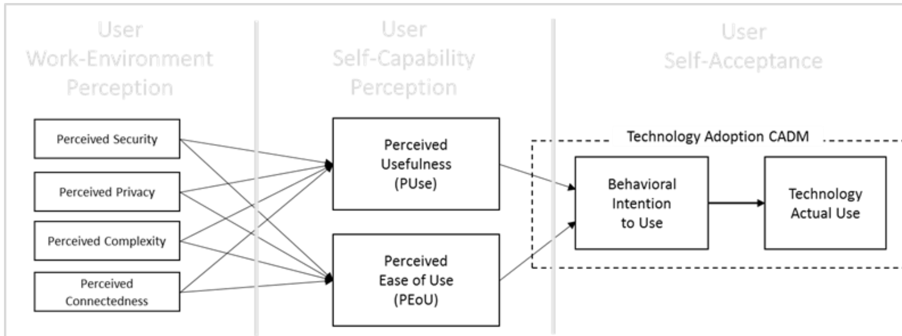


Figure 4. ETAM framework structure.

Figure 4 shows TAM constructs PU and PUoE influenced by the external predictors of PeS, PeP, PeN, and PeC. My literature review would encompass thorough information related to the research topic. Hence this required an in-depth synthesis based on previous dissertations, journals, and articles that used ETAM frameworks to analyze the intention of use of technology based on the variance of PU and PUoE affected by external factors. Therefore, extending a detailed summary of cloud computing and argumentatively considering some of its benefits for discussion as a necessity to prove on how TAM ties the constructs of other theories and external factors into one framework of ETAM. The literature ETAM of my study stemmed from the theoretical design proposed in Figure 3. The predictors PU and PEoU were used as core items of the ETAM framework and would assist as mediators between the independent variables PeS, PeP, PeC, and PeN and the dependent variable, namely IUoT of my study.

It was revealed in previous scholar studies, that the external influential factors PeS, PeP, PeC, and PeN stem from several theories related to technology acceptance such as Diffusion of Innovation theory (DOI), Technology-Organization-Environment (TOE) theoretical model, and UTAUT theory (Changchit & Chuchuen, 2016; Gangwar, Date, & Ramaswamy, 2015; Hsu, Ray, & Li-Hsieh, 2014), however the independent variables of study may curtail the top concerns of security, privacy, complexity, and connectedness that impact the decision making and directly affect the IT solution architects' and IT managers' intention of use, and therefore their PU and intentional adoption of the cloud computing services (Davis et al., 1989).

Operational Definition of Variables

I utilized for this correlational quantitative research study a survey questions using a Likert Type scale that would allow collecting raw numerical data, based on which statistical procedures of analysis would help to identify the relationships between the TAM variables. Bell, Bryman, and Harley (2018) illustrated that the Likert Scale, being an ordinal psychometric instrument of measurement of attitudes, beliefs, and opinions, is convenient to quantitative correlational analysis. Field (2017) stated that the good side of the Likert Scale is that it is one of the universal methods for survey collection, and is easily understood. I customized a questionnaire from a previous and valid and tested survey instrument that was used to perform a cross-sectional survey for IT managers that were facing challenges adopting cloud computing in Afghanistan (Jones, Irani, Sivarajah, & Love, 2017). These four influential independent variables PeS, PeP, PeC, and PeN were tested and analyzed to check their effect on the mediator variables of TAM PEoU and PU and what their positive or negative impact was on the IUoT maturity.

IUoT. This construct demonstrated the intention to which a technology solution architect was willing to use cloud computing within the organization. IUoT was measured by an interval variable ranging from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert scale (Joshi, Kale, Chandel, & Pal, 2015; Xu & Leung, 2018). Therefore, a higher score indicates high levels of the intention of adoption of CCS, while a lower score indicates lower levels of the intention of adoption.

PEoU. This variable referred to the level to which technology users perceived that using technology would be free of effort (Davis et al., 1989). In other words, that was the ease of capturing, learning, and using CCS. PEoU was measured by a single interval variable ranging from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert scale (Joshi et al., 2015; Xu & Leung, 2018). A higher score indicates that CCS is perceived as very easy to learn while a lower score indicates the cloud is perceived with low levels of ease of use.

PU. PU denoted the degree that users believe the adoption of CCS would improve their computing daily operational work (Abdullah, Ward, & Ahmed, 2016). PU was measured by a single interval variable ranging from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert scale (Joshi et al., 2015; Xu & Leung, 2018). The higher score for PU indicates that CCS is perceived as highly useful, while a lower score indicates CCS is perceived with lower usefulness.

PeN. PeN raised the level to which Internet connection quality would qualify the completion of CCS transactions, as being a vital factor to accept using a cloud-hosted application. The quality of Internet connection was an interval variable ranging from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert Scale (Joshi et al., 2015; Xu & Leung, 2018). A higher score indicates that CCS is perceived with a lower level of concerns about Internet connection quality while a lower score indicates CCS is perceived with higher levels of concerns about Internet quality.

PeS. This variable referred to the level of confidence of a solid security setup of perimeters and power processing components against the external and internal unauthorized access. PeS was a single interval variable that ranges from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert Scale (Joshi et al., 2015). A higher score indicates that the cloud is perceived as highly secure, while a lower score indicates that the cloud is perceived with lower levels of security.

PeP. PeP raised the degree of confidence that users have in CCS providers' honesty, integrity, and the operational processing setup. PeP was a single interval variable that ranges from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert Scale (Joshi et al., 2015). A higher score indicates that the cloud is perceived as a podium with a high privacy setup framework, while a lower score indicates that the cloud is perceived with lower levels of privacy.

PeC. PeC refers to the level of extra efforts users should exert to familiarize themselves with the new systems of CCS to accomplish their daily tasks easily (Spence & Wang, 2018). PeC was a single interval variable that ranges from 1 (strongly disagree) to 5 (strongly agree) on the five-point Likert Scale (Joshi et al., 2015). A higher score indicates the cloud is perceived as a podium with high complexity and difficult to familiarize with while a lower score indicates the cloud is perceived with lower levels of complexity.

As such, these dependent variables and the TAM would compose this study framework of Enhanced Technology Acceptance Model (ETAM), which would contribute to this study by developing and testing it. In this literature review, the cloud adoption general problem was presented, which was followed by a description of the technical and commercial designations, uses, and benefits of cloud computing. The review lingers through a discussion about the factors that influence the cloud adoption decision, the cloud computing application, and the challenging factors about SMEs' propensity to adopt cloud technology. The focal point of the literature review was the research questions, as well as other critical influential factors such as cloud privacy and security concerns. The literature review constrained the discussions around the developed ETAM of the study. In addition to this review, this study would include in-depth synthesis discussions about the prominent parametric features influencing the cloud computing adoption decision such as cost-efficiency, elasticity, availability, performance, and integration. However, it still valuable to discuss these key beneficial terms of cloud computing in this review.

The focal point of the literature review was the research question:

RQ: Is there a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with the intent to adopt CCS?

From the research question, I developed the following null and alternative hypotheses:

H_0: There is no relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

H_a: There is a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

I focused the literature review on four key areas: (a) IT Problem - cloud computing lack of adoption by SMEs, (b) the benefits of cloud computing, and (c) the application of TAM to cloud computing. My research on cloud computing centered on the CCS history of use, SMEs issues using cloud computing, and arguments concerning benefits and advantages. A further composed subsection of this review, I elaborated on the ETAM framework focusing on explaining how the variables of security, privacy, complexity, and connectedness towards PU and PEoU led to the application of intent of use and adoption of cloud computing services.

Introduction to Cloud Computing

The overarching theoretical concept of carrying computing powers based on shared resources of IT through a universal cloud network developed in the 1960s (de Bruin & Floridi, 2017; Xu, Tian, & Buyya, 2017). de Bruin and Floridi (2017) stated that cloud computing should become a daily commodity of technology like telephony. However, the cloud computing development progress lapsed for two decades between the 1970s and 1990s. The CCS developments lapse, and according to Jeong, Yi, and Park (2016), were due to computer manufacturing paradigm, which lacked compatibility, strong compactness, and affordability for individuals as well as for organizations.

Moreover, the application software design and rationale for insourced hardware infrastructure, known as IT legacy architecture, presented another challenging dilemma. SeetharamaTantry, Murulidhar, and Chandrasekaran (2017) added that the unchanging legacy of software components and applications rationale raised another limitation to cloud computing progress since the 1970s. Jeong et al. (2016) added that Internet development and high bandwidth accommodation played a serious role to resolve limitations and improve CCS after the 1990s.

During the last two decades, cloud computing surpassed many architectural developing changes starting with the 1st stage of delivering small individual servers of limited resources, the 2nd stage of massive resources capacity through sophisticated in-house data centers, and 3rd stage by proposing the distributed power computing, data storage, and on-the-shelf applications through cloud computing mechanisms. Modic et al. (2016) explained that CCS matured as an enabler for an outsourced model of power processing and data storage infrastructure. Roman, Lopez, and Mambo (2018) revealed a fundamental gap proposing that CCS maturation requires a reformation of cloud security. Rao and Selvamani (2015) praised CCS as being a developed platform to provide consumers with the ability to store and retrieve data to and from the cloud, including mobility anywhere, and to access the cloud application through the Web. Rao and Selvamani (2015) honored CCS as being a disruptive innovation, emphasizing that any challenges such as security and privacy would be solved through time.

Furthermore, CCS was perceived as a disruptive innovation as it appeared to be a platform for IT with substantial resources indorsed for individuals and enterprise businesses. The technology concept had been fundamentally welcomed because most organizations were looking after professional service delivery of IT resources of high performance, high scalability, and cost-efficiency (Ali, Wood-Harper, & Mohamad, 2018; Garrison et al., 2015; Hashem et al., 2015; Wang, Y., Chen, & Wang, D. C., 2015). The historical background of IT paved the road to this innovation, as organizations suffered the high cost of insourcing their own data centers to accommodate necessary IT resources and run their applications and operational services. IT resources require high maintenance skill that incurs significant expenses for small and medium-sized businesses (SMEs). The owned IT resource and infrastructure performance healthcare include fulltime IT skilled expertise, computing equipment with limited excess capacity, security setup, third parties continuous support, and other related outsourcing services that SMEs prefer to avoid because of associated high cost (Garrison et al., 2015; Hashem et al., 2015).

According to various statistical surveys of the market, the cloud industry increased the size of its service offerings (Darwish, Hassanien, Elhoseny, Sangaiah, & Muhammad, 2017). One of the key advantages of CCS was affordability; Nayar and Kumar (2018) confirmed that virtualization, resource sharing, and economies-of-scale allowed a significant reduction of power computing unit price. CCS presented its products to markets through various convenient payment models such as pay-as-you-go, where the value proposition became importantly attractive to SMEs. He, Cheng, Wang, Huang, and Chen (2017) defined CCS as being a subscription-based-service utilization of computer hardware and software over the Internet. Di, Kondo, and Wang (2015), from the same perspective, defined CCS as being known as the outsourcing model of on-the-shelf computational service capacity, and data storage location transparent cloud. Poola, Ramamohanarao, and Buyya (2016) supported such definitions by adding that CCS was understood as being a multi-redundancy data center delivering IT active services of enormous capacity and scalability, accessible from anywhere, and located anywhere the world.

Brinda and Heric (2018), in a Bain & Company report analysis of the title "*The Changing Faces of the Cloud,"* revealed that cloud services IaaS and SaaS captured 60% of IT market growth, mostly in the public cloud space. Gangwar et al. (2015) supported the CCS market growth but reported few challenges of the cloud industry. Gangwar et al. (2015) provoked a similar declination of CCS demand by presenting patterns of growth in some areas that stood stagnant despite the business need. Chang, Kuo, and Ramachandran (2016) showed the intensive market need to cloud services and mentioned about a slowdown in CCS growth due to fundamental factors impacting CCS adoption. Brinda and Heric (2018) explained that the early adopters fueled the first waves, but then overtaken by a larger mainstream of customers who took a wait-and-see approach. Abrar et al. (2018), in their CCS risk analysis, revealed several challenges but confirmed the need for SMEs to IT high performing services due to many encouraging benefits such as cost reduction, availability, and on-demand scalability. Gangwar et al. (2015) in his study confirmed such a need for SMEs. Gangwar et al. (2015) positioned the nonadopters of CCS as laggards keeping CCS adoption a year-on-year strategic objective. The laggards nonadopters of CCS, need more time to trust new technologies, so they revisit the decision every time for more in-depth analysis to find a better strategy for adoption.

Therefore, this study should be instrumental in revealing some key barriers and concerns that boost IT solution architects and managers' reluctance to adopt CCS and commit of practical usefulness. Srivastava and Nanath (2017) confirmed that such an analysis of problems and challenges discussed in-depth would allow IT architects and their managers to gain trust in the concept idea of cloud computing. For some IT architects, CCS was a new skeptical paradigm, because it was based on a virtualized architecture of IT shared resources that allow CSPs to offer highly competitive products and services based on a dynamic resource sharing model. Chang et al. (2016) fully supported the positive impact of analyzing and discussing technological challenges on nonadopters. In this section, I will elaborate with more details on virtualization architecture, essential features, and service models of cloud computing services.

Cloud Security

Several studies on cloud computing challenges demonstrated security and privacy as being the major challenges that constrain CCS practice and adoption acceptance. CCS architecture being a paradigm different from the traditional call centers of computing and storing of data, where owners are in full control of storage and computation. CCS requires physical data management and machines privileged administration to be delegated to the CSP while data owners and customers only retain limited control over their virtual machines. Thus, the accuracy of processed and stored data and related computation might be compromised due to the lack of necessitated control and setup of data security frameworks (Hussein & Khalid, 2016; Stergiou et al., 2018). Khan (2016), in his article survey of security issues of cloud computing, concluded that enterprises are required to verify security compliance, whether it conforms to the regulations and standards security framework, including regular auditing practices. Many research studies agree on a universal consensus that data storage and processing power is fluid in CCS and may reside on any available computing VM and storing capacity of the cloud-net. Such diversity of computing delivery models based on resource pooling that shifts everything on the distributive environment makes CCS more vulnerable to security attacks than any other computing platform. Hence, CCS vulnerability could be exposed by any component architecture of the ecosystem such as network, virtual machines, storage and applications, which can be used as a basis to cyberattacks (Botta, De Donato, Persico, & Pescapé, 2016; Ramachandra, Iftikhar, & Khan, 2017; Singh, Jeong, & Park, 2016). Singh et al. (2016) revealed the risk of the security in his survey by illustrating statistics about 70% of an increase in Advance Persistence Threat (APT) attacks, 68% suspicious activities, and 56% type of brute force cyberattacks against cloud environment networks in 2015. An APT is a cyber network attack where an undefined identity intrudes unauthorized access to systems and stays unnoticed for an extended period (Chang et al., 2016). The International Data Center (IDC), research and analysis institutes surveyed more than 244 CIOs on cloud challenges and concluded that security is most concerned topic for 87% of respondents (Ramachandran & Chang, 2016; Senarathna, Yeoh, Warren, & Salzman, 2016; Singh et al., 2016). Therefore, Chang et al. (2016) confirmed that security issues hampered some business organizations who became reluctant to believe the CSPs and hesitate to adopt critical services. Ali, Khan, and Vasilakos (2015) stated that security in cloud computing is applied through security frameworks, policies, and SLAs as a foundation to the expectation of cloud service delivery between the customer-organization and the CSP. However, most times, security frameworks are not accurately applied, and accordingly, most IT professionals commonly believe that cloud computing is mechanisms that distribute data openly at much higher risk.

Hence, the question of the reliability of data protection by using the concept of cloud computing still a significant deterrent. As a conclusion, for confident use of cloud computing by customers, the level of data security has to be increased by applying security best methods and practices such as cryptographic methods. For an efficient cryptography setting, all types of client's data processed within the cloud hosting services should be firmly encrypted. Moreover, cryptography includes data-transfer process client-to-server and vice-versa through secure interconnectivity setting as it is vital to use secure tunnels of data transfer to access cloud resources.

Cloud Privacy

Information privacy is defined as being the right of every person to allow or to ban the use of information about him, and hence the information sharing should follow clear rules (Zhou, Cao, Dong, & Vasilakos, 2017). It is difficult for security professionals to define significant differences between privacy and security (Sicari, Rizzardi, Grieco, & Coen-Porisini, 2015). Privacy is understood as the ability to protect the sensitive personal information of individuals and organizations, while the protection of information is a security component. Botta et al. (2016) clarified in his study that at any time, personal information is used without following the privacy policy rules, is treated as a breach of information privacy. El-Gazzar, Hustad, and Olsen (2016), in their study using the Delphi approach for in-depth cloud adoption analysis, found that cloud services are being criticized mainly due to privacy and availability concerns that outweigh by far the benefits. Several other research studies concluded that privacy is one of the main factors barriers to cloud adoption in many countries (Khan & Al-Yasiri, 2016; Raza et al., 2015).

For the cloud's stored data, the privacy risks can be seen relatively shared between three primary stakeholders: (a) Privacy individuals, for individual users of small volume of data on the cloud; where the risk to access the personal information of the cloud-user is intrusive if it happens without the user notification or asked for approval. (b) Privacy enterprise, for organizations hosting business information on the cloud, where the risk to access business, information is of much larger drawbacks as the information leakage affects the enterprise reputation, market share, market value, and violation of regulations very badly. (c) Privacy CSP, for service providers facing customers that are a victim of privacy violation, where the risk is to lose the business, trust, and confidence of IT professionals planning to adopt CCS. Also, for any of those violation's categories of privacy protocols, the incident may get followed by severe lawsuits due to the failure to conform to local regulations (Henze et al., 2016).

In summary, cloud's hosted data privacy issues, if accidentally violated, it can impact cloud adoption rate directly, and unwaveringly it can entirely dash down the trust and confidence level of the cloud stakeholders, existing customers, and future cloud adopters, in addition to severe implications from legal, economic, and personal perspectives.

Cloud Service Complexity

Cloud computing solutions provide an ample volume of benefits. However, complexity remains an issue. Tripathi and Nasina (2017) identified six game-changing business enablers powered by cloud computing, namely: cost flexibility, business scalability, market adaptability, masked complexity, context-driven variability, and ecosystem connectivity. Phaphoom et al. (2015) represented a cloud computing study that aimed to understand the impact of specific technical barriers on the decision to adopt cloud services in an organizational context, namely availability, portability, integration with current enterprise systems, migration complexity, data privacy, and security. Phaphoom et al. (2015) emphasized that complexity of cloud computing services appears in too many phenomena such as IT infrastructure architecture, integration with current systems, data migration, ecosystem's applications interoperability, financial issues, and evaluation of benefits as well as general security setup. Pedone and Mezgar (2018) analyzed a more profound insight into complexity by examining the operational standardization process. Pedone and Mezgar (2018) measured the service lifespan and checked the integration interoperability between the cloud service and the systems in the organization. In their measurement outcomes, Pedone and Mezgar (2018) found that the complexity lies in the cloud service's dependencies on business processes and the volume of efforts and planning required. Rogers (1996) defined complexity as being the extent to the innovation, or the new solution is perceived to be challenging to understand and use. However, Shiau and Chau (2016) in their study found that the effects of complexity usage on the PU as well as PEoU of e-learning is significant and demonstrated to be a barrier of adoption by some colleges. Gutierrez, Boukrami, and Lumsden (2015) examined eight factors that only four of them had found a significant influence on the adoption decision of cloud computing services in the UK. Those four key factors of Gutierrez et al. (2015) study include complexity. However, complexity was one of the two most significant factors for the adoption decision. In a case of Helix Nebula, Nowakowski et al. (2018), in a study of understanding and guiding the IT ecosystem dynamics and complex service ecologies, escalated complexity as being a value-destroying of technology platform with users' socio-technical interactivity. Therefore, Blaschke (2019) explained that such complexity increasingly inhibited the digital platform of Helix Nebula from thriving and growing, where Helix Nebula faced the situation by applying significant modifications and adjustments to its platform to reduce its socio-technical complexity and facilitate business growth.

Cloud Connectivity

CCS, being an Internet-based technology; it requires a reliable, stable, high quality, and enough bandwidth Internet (Guerrero-Ibanez, Zeadally, & Contreras-Castillo, 2015). The main problem lies in the high cost of Internet bandwidths in some developing countries, which remain prohibitive (Chavez, Littman-Quinn, Ndlovu, & Kovarik, 2016). However, due to operational expenses constraints, the CCS need for high-quality internet connections became an influential critical factor on the rate of adoption by SMEs. Connectedness is a term that encompasses both high quality and high bandwidth connection between organization systems and cloud computing virtual and physical platforms. During peak-times of operational services, the mandate of a cloud computing user is to have a reliable Internet connection to access IT resources at remote data centers. Therefore, adequate bandwidth, high stability, and high availability are essential characteristics of a reliable connectedness to accommodate the real-time services that involve substantial data client-server exchange and require significant processing power. Reliable connectedness characterizes the quality of Internet connection needed to render the CCS adoption possible to an organization. The quality of Internet connection or constant connectedness is the degree to which the internet connection will allow users to perform as usual and complete their CCS transactions.

Other Challenges to Cloud Computing Adoption

Other than the variables of study, security, privacy, complexity, and connectedness, there are too many other factors that may inhibit cloud computing intention of adoption. In this section, I would like to mention some of them informatively:

Cost model. It has been stated before in this chapter that cost-effectiveness is one of the main CCS' advantages, as it reduces data centers' capital and operational expenditures of power computing and data storage infrastructure significantly. However, some researchers extended their study of cloud cost-effectiveness to reveal that cloud services adoption causes proportional cost decrease; as while reducing data centers TCO from one side, that from another it roots other costs to increase such as:

Complex resource management. Cloud applications are designed for multi-resource configurations to optimize computing and storage shared-resource allocation. The CSP committed to an agreed SLA of availability, performance, and dynamic capacity. The resource demand to apply to the required return is application-dependent, and that makes the optimized resource management complicated, mainly when the multi-resource size configuration is large (Xu, Yao, & Jacobsen, 2018; Ran, Yang, Zhang, & Xi, 2017; Madduri et al., 2015).

End-to-end service interconnectivity. While CCS is embraced as IT computing resources based on cost-cutting measures, the end-to-end infrastructure cost setup, if not measured may reveal as a severe cost-increase problem. There are several research studies (Abou-Shouk, Lim, & Megicks, 2016; Ishola, 2017; Obinkyereh, 2017; Tan, Ng, & Jiang, 2018) on technology adoption in developing countries. Most of those research demonstrated that a nonstandard environmental factors such as unstable telecommunication infrastructure, weak coverage of internet, inadequate and unreliable operational SLA, slowness of the mobile network technology roadmap expansion, and the high cost of Internet bandwidth, in addition to the political and economic instability are significant barriers to cloud computing cost efficiency (Abou-Shouk, Lim, & Megicks, 2016; Faqih, 2016; Li, M., Qin, Li, J., & Lee, 2016; Tan, Ng, & Jiang, 2018).

Security setup. Sookhak, Gani, Khan, and Buyya (2017), in their study of cloud data security, demonstrated that a reliable security setup for the cloud architecture requires dynamic update operation that incurs an expensive computational cost. Besides, several other studies revealed security challenges related to the demand for scalability and manageability of security countermeasures such as routers configuration, firewalls, and intrusion detection nodes. Hence, such tight integration and dynamic resource allocation to adapt to security measures are a difficult undertaking, that for an appropriate deployment, it would tremendously increase the cost (Lorenz et al., 2017).

In summary, the cloud cost efficiency factor should follow an end-to-end cost model entirely depending on the in-country environmental conditions and scenarios, as the developing countries do not support any deployment standard counter to the developed countries, who usually root the technology to (Chou, 2015; Senyo, Addae, & Boateng, 2018).

Charging model. Previous paragraphs revealed the flexibility of cloud offers and their adaptability to the as-you-go real-time and dynamic charging models. Therefore, the cost analysis has become complicated, and a customer who is not profoundly aware of the right dynamic-per-demand resource would face difficulties in selecting the most convenient model for his IT environment (Chekired, Dhaou, Khoukhi, & Mouftah, 2018). Such a multitenancy cost model, especially for SaaS deployment in large volumes, may induce an unmanageable complexity of its dynamic charging versus the cost-efficiency expected. Ran et al. (2017), in their study analyzing the cloud dynamic charging problem, proposed a complex algorithmic intelligent control to dynamically re-design, and cap the capacity through real-time recalculation of computing resources for immediate allocation of instances to optimize IT resources availability. Ran et al. (2017), admitted that dynamic capacity expansion might lead to undesirable cost expansions, and hence, quality and security reinforcements would raise the charging rates and volumes.

Service Level Agreement. Cost is not the only key objective for IT customers to migrate to the cloud. Hence to guarantee high quality, high performance, and reliability of services, the cloud users need to have an SLA that provides them an operation of a standard of quality of service that meets with their expectations. SLA is a contractual and operational mean of assurance that the maximum expectations of a cloud customer are met and that service offer capacity complies with the cloud computing power and allocation of resources. The SLA framework must cover key business concerns such as operation governance, SLA control and feedback, resource upgrades, cost versus capacity optimization, customization mechanism of infrastructure and software solutions, new features of PaaS and SaaS, and technology change and development (Hussain, W., Hussain, F. K., Hussain, O. K., Damiani, & Chang, 2017; Singh, Chana, & Singh, 2017).

Cloud interoperability. The interoperability within the context of CCS is the enabler providing the cloud ecosystem to be widely adopted by individuals and organizations in such a fashion that multiple cloud platforms can exchange information in a unified manner. The interoperability feature of CCS is vital as it encourages adoption and ensures smooth data flow across different clouds to enhance the data flow structure between local applications (Pérez, Zambrano, Esteve, & Palau, 2017). Cloud integration with interoperability enabled requires to fulfill the following: (a) Rebuilding the customer application stack in the new cloud platform. (b) Set up network configuration to provide the application stack same performing support it had in the original setting. (c) Set up a security baseline to match the original or better protection capabilities. (d) Apply administrative management of knowledge of the application stack. (e) Handling data safety and movement through methodic encryption mechanism of data for internal and external transit (Nodehi, Jardim-Goncalves, Zutshi, & Grilo, 2017). According to Song (2017), the cloud interoperability operates within all the layers and levels of clouds' running assets and computing resources. Such interoperability mechanism is needed to cater for information availability with fast-access, for which organizations are paying the need to keep their applications setup intact within a logically secured periphery. Pedone and Mezgar (2018), in their study about the affinity of cloud interoperability, mentioned that cloud computing is at its infancy, and the issue of interoperability still did not appear within the global industry of cloud computing.

In summary, there was a severe need for the organizations to move to the cloud and enjoy its benefits, but still, some serious challenges preventing the fast adoption of CCS. Organizations had main concerns about security and privacy to migrate to the cloud. Most organizations favored SaaS rather than IaaS, for one fact that many of the marginal functions were hosted and migrated to cloud whereas, the essential features and critical applications were kept in-house (Kabbedijk, Bezemer, Jansen, & Zaidman, 2015; Safari et al., 2015). Also, some research studies have shown that 30% of organizations planned to adopt cloud storage services in the next three years, but still, it is to be improved a lot (Palos-Sanchez, Arenas-Marquez, & Aguayo-Camacho, 2017; Wu, Rosen, Wang, & Schaefer, 2015).

Cloud Computing Service Architecture

In a cloud computing architecture, all running applications are under control management fully monitored and served by the cloud servers' virtual threads. The data is fully replicated and preserved remotely as part of the cloud configuration. A well-integrated cloud ecosystem can provide limitless efficiencies and resource scalabilities. Several key elements of cloud architecture rendered the cloud concept very successful, such as the resource virtualization mechanism, the service architecture model, and other essential features that I will present in this section.

The concept of virtualization. Back in history to the 1990s. Information technology data centers used to run entirely on bare-metal physical servers and accommodate single-vendor per IT stack, a limitation that would never allow legacy applications to run on a different vendor's hardware (Vithayathil, 2017). Mijumbi et al.

(2016) confirmed that network virtualization provides a potential of significant reductions in operating expenses as well as in capital expenses, as it facilitates the provisioning of new services with high agility and faster time-to-value. Chen, Zhang, Hu, Taleb, and Sheng (2015) in their study about the cloud-based virtualized fourth and fifth-generation wireless network, found that companies had been used previously to update and refresh their IT environments with more convenient commodity servers, operating systems, and applications from a large variety of vendors. Inevitably, those companies get bound to an underuse physical hardware as every single server of their computing power could only run one specific vendor-task. As such, it is understood that hardware manufacturers perceived the fundamental need for virtualization, being a solution resolving two main problems: (a) efficient use of server capacity, and (b) partitioning of bare-metal servers' resources to run several applications on multiple operating systems.

Therefore, and as a simple definition, virtualization is an innovative technology that allows system administrators to create useful virtual and logical IT computing power using physical resources that are bound to hardware. The bare-metal virtualization technique allows companies to use a physical machine's full capacity by distributing the available capabilities among many users or environments flexibly (Ali et al., 2015; Swathi, Srikanth, & Reddy, 2014). Thakur and Mahajan (2016), in their article entitled Virtualization in Cloud Computing, revealed few details about benefits and advantages of virtualization to computing power such as (a) Resource Maximization, where the virtualization conceptually permits most extreme utilization of the hardware speculation.

(b) System proliferation, where virtualization allows to run multiple types of applications with different operating systems on the same physical hardware. (c) Flexibility, where virtualization facilitates a dynamic, demand-driven allocation of computing power as well as fast migration of servers. (d) Availability, where virtualization increments accessibility through dynamic provisioning and movement of basic frameworks based on real-time hypervisor control of the virtual machines. (e) Scalability, where virtualization distributes the computing resources dynamically based on the running application demand. When demand increases, the hypervisor creates a virtual guest or instance operating system to achieve the scalability required. (f) Optimized hardware utilization, where virtualization allows to use computing assets that are left idle and provides an increased utilization ratio of resources as high as 80 percent, and hence it reduces the hardware requirements by a rate of 10:1 or better. (g) Security, where virtualization confines benefit by running isolated administration privilege on each virtual machine, such an approach is called jailing of services.

In conclusion, cloud computing without the virtualization technology is possible as a concept, but it will be inefficient and inflexible and makes CCS unreliable as a solution. Virtualization is an essential feature as it supports CCS with flexible adaptability, versatility, and dynamic scalability and cost-efficiency. Virtualization management governs the computing resources and controls related optimization of use; it adapts fast, versatile provisioning of on-demand virtual machines and provides a flexible application programming model. Such management capability, rendered the virtualization a key feature as it enables technology to create an intelligent abstraction layer that buckskins the complex maintenance administration of the underlying bare-metal hardware and operating system software.

Other essential features of cloud computing. The cloud setup is composed of five critical service features well known as on-demand self-service, broad network access, IT resource pooling, rapid elasticity, scalability, and controlled and measured services (Manuel, 2015; Ren, Zhang, Wang, Tao, & Chai, 2017; Yan & Yu, 2015). The on-demand self-service states the ability of the cloud user to request for more computing capabilities of server resources and network storage. With the on-demand self-service mechanism, CCS complies back with delivering these resources with limited human interaction (Alvarez, Mirzoev, Gowan, Henderson, & Kruck, 2017; Daylami, 2015). The broad-network-access service denotes the ability of cloud computing resources to be easily accessible. This broad-network-access feature is used through the standard Internet access infrastructure that includes mobile applications thick clients as well as the standard computer browsers thin client (Yan, Yu, Gong, & Li, 2016). The resource pooling feature designates the merging mechanism of computer resources in one managed stack. The resource pooling architecture allows serving a multitenant model where all physical and virtual resources are automatically allocated and reallocated based on the ecosystem demand (Wood et al., 2015). The rapid elasticity is an essential feature of cloud computing as it refers to the aptitude of cloud allocation and reallocation of resources dynamically and elastically. The rapid elasticity feature tolerates consumers to request automatically and, on the spot, additional computing resources such as storage space or extra processing power. Hence, rapid elasticity is a key aspect of CCS because the resources appear to be unlimited with high availability (Kaur & Chana, 2015). The measured service feature refers to the logging, monitoring control, and optimizing of the resources through a metering functionality of abstraction services such as storage space, bandwidth, memory usage, and processing capacity (Wood et al., 2015).

The cloud computing service had efficiently added an extraordinary performance to the provisioning mechanisms of the cloud features (Madduri et al., 2015). In a non-cloud or legacy data center environment, when the consumer submits an order provisioning with or without human interaction through the IT provider, the supply chain becomes very complicated and order-after-order it becomes impacted (AWS, 2018). The legacy architectures of silo data centers are managed through semi-automated capacity management, and the planning is performed through a secluded labor-intensive structure that lacks control. Such administrative legacy function performs with little or no communication between decision-makers and stakeholders. Hence, the downstream effect of such process behavior shows inefficiency and waste of resources and time (Gutierrez et al., 2015).

Cloud computing service models. There are usually three service models in cloud computing offered to the market consumers to compare: The software as a service (SaaS), the platform as a service (PaaS), and the infrastructure as a service (IaaS) (Hashem et al., 2015; Kirubakaramoorthi, Arivazhagan, & Helen, 2015). The SaaS model helps users to have access to service software through the web internet running on the cloud servers rather than having the application implemented on the premises. SaaS offers numerous advantages to companies by significantly dropping the time and money to spend and achieve tedious tasks to install, manage, and upgrade software on-premise (Goutas, Sutanto, & Aldarbesti, 2016; Huang, Ganjali, Kim, Oh, & Lie, 2015). The service model of PaaS is very similar to SaaS, except instead of carrying the software accessible over the internet. PaaS provides access to a platform for customer-owned software creation over the web, and through which PaaS customers' developers will have the freedom to focus on building the software without worrying about hardware, operating systems, software updates, storage, or infrastructure (Alhamazani et al., 2015; Yangui & Tata, 2016). IaaS offers cloud computing infrastructure to organizations such as servers, networks, operating systems, and storage through virtualization technology. IaaS services are provided to customers through APIs, where the clients have complete control over the entire infrastructure (Serrano, Gallardo, & Hernantes, 2015). Moreover, IaaS provides the same IT capabilities as a traditional data center.

Statistical surveys in developed countries revealed that Amazon Web Services; that provides accessibility to the Amazon Elastic Compute Cloud (EC2) to get integrated to cloud services IaaS, SaaS, and PaaS, revealed that Amazon AWS generated $3.2 billion in revenue in Q3 of 2016 alone, with an increase of 55% over the same period in 2015 (Statista, 2017). Similar statistics revealed that Microsoft Azure trail far behind AWS, and that market growth of cloud products is expected to account in return 30% of cloud companies' revenues by 2018 (AWS, 2018; Microsoft Azure, 2018). From a consumer side, surveys illustrated that about 41% of businesses are planning to partially or entirely migrate services to cloud technologies, and that with 51% of big-to-midsize enterprises compared to around 35% of SMEs.

Cloud computing deployment types. The cloud industry is presented through four different types of cloud deployment models: private cloud, community cloud, public cloud, and hybrid cloud (Botta et al., 2016; Goutas et al., 2016; Schneider & Sunyaev, 2016). With the private cloud type, the architecture computing infrastructure is provisioned for one single organization holding one or multiple business units. Typically, the said organization owns, operates, and manages the private cloud infrastructure, and the cloud solution may or may not exist on the premises. In the public cloud, the infrastructure is maintained by third parties, and based on the requirement computing need the IT resources are provided. So, in cloud public model, the infrastructure is built on an owned-premise of the cloud service provider. In the community cloud, the infrastructure is provided to a specific community of organizations of shared concerns. Hence, in such a model, a single or combination of organizations form the community and provide the operational management of the community cloud. However, the hybrid cloud model is a combination of any two, or all, of the three mentioned models. In other words, some systems of the hybrid cloud can be placed in the public domain, and some other systems can be in the private cloud domain. Srinivasan, Quadir, and Vijayakumar (2015) explained the hybrid cloud by providing an example as being the data component storage of a set of applications that reside in a private cloud, while the business logic applications reside in the public cloud. Therefore, a hybrid cloud is a viable methodology to protect consumer information and isolate the data environment to increase security and privacy safety.

Benefits of Cloud Computing

Wang et al. (2015) demonstrated the cloud computing technology as being a disruptive and revolutionary transformation of IT that revolted the digitization era and provided individuals and business operations ease accessibility to services. Several studies of analysis, such as Martins, Oliveira, and Thomas (2016) as well as Novkovic and Korkut, (2017), have demonstrated that CCS due to its flexible architecture and ease accessibility can provide a large catalog of benefits such as:

Resource optimization management. In IT on-premise data centers, IT resources of the power computing are used ineffectively. IT managers perceived that the adoption of cloud computing services, especially IaaS and PaaS, could result in significant savings of capital expenditure. For the cloud computing services, the cloud provider owns and maintains the bare-metal physical infrastructure, and manage a virtual pooled shared resource where customers pay a subscription fee for the dedicated use of on-demand resources: Use-as-per-Need and Pay-as-per-Use. Moreover, Maresova and Sobeslav (2017) presented a thorough analysis of a study about an effective evaluation of cloud investment’s return. Maresova and Sobeslav (2017) illustrated that the adoption of cloud computing provided the capacity to offer to individuals and businesses the facility to virtually own a scalable IT infrastructure and applications through IaaS, PaaS, and SaaS services. The cloud services mechanisms entailed huge asset venture that if wanted to be created within the company premises, it would involve tremendous investment.

Cost efficiency management. The primary driver and key benefit of cloud computing adoption for SMEs enterprise businesses is the cost-efficiency (Gumbi & Mnkandla, 2015; Jeong, Park, Lee, & Kang, 2015; Li et al., 2016). Gu, Zeng, Guo, Barnawi, and Xiang (2017), in their study about cost-efficient resource management on fog computing, encouraged the cloud adoption versus cost reduction. Gu et al. (2017) highlighted that the right strategy of Cloud adoption might reduce the costs related to the IT cloud resources such as software licenses, hardware operation, and maintenance as they are remotely accessed whether through API or web-access. Hameed et al. (2016) as well as Kaleem et al. (2017) in their studies of cloud computing impact on energy saving, revealed that most IT managers are aware of their budget impact by 18% to 20% of average reduction once business services are shifted to CCS. Moreover, Hameed's study emphasized that out of these operational expenditures savings, 16% are observed in data center power costs. Steve Jones et al. (2017) investigated risks versus rewards of moving business and operational services to CCS in the United Kingdom, emphasized that the government organizations of the UK have been shifted to CCS to reduce the total investments in IT operational infrastructures and the total cost of ownership (TCO). Hsu et al. (2014), in their study concerning the real intentions behind CCS adoption, found that IT managers of small and medium-sized organizations realized the pain of spending year-on-year to sustain the deals of software and licensing services for their data centers, including end-user office software running on desktops and laptops. CCS products can make such legacy deals unnecessary and therefore decreases the expenses of the business IT infrastructure.

Information distribution management. Cloud computing provides colossal abilities to store and process all types of information, and it manages the distribution of information pervasively in a ubiquitous manner through redundant complementing ecosystems (Puschel, Schryen, Hristova, & Neumann, 2015). Yang, Huang, Li, Liu, and Hu (2017) said the cloud elaborated on the difficulties of Big-Data and related challenges it presents for digital solutions to store relevant information, transport, process, mine, and store the data. Li et al. (2016) as well as Wang, Ma, Yan, Chang, and Zomaya (2018) performed in-depth studies about cloud computing information distribution management related to big data and concluded a common finding that CCS provides fundamental support to address the challenges with high capacity of shared computing resources that include storage, networking, and analytical software. The application of fog computing and shared resources of the cloud has fostered impressive big-data advancements. As per Puschel et al. (2015) and several other study findings, demonstrated the cloud computing as a flexible and agile data management competencies in several industries of the market such as supply chain, customer management, business intelligence, marketing management, and electronic healthcare systems that demonstrated considerable success of increasing efficiency for businesses (Bajaber et al., 2016; Opara-Martins, Sahandi, &

Tian, 2016; Vasiljeva, Shaikhulina, & Kreslins, 2017). In summary, business data are stored through PaaS and SaaS cloud services, processed, mined, updated, stored, and retrieved effectively, and hence, CCS allows most business sectors' professionals to execute their tasks resourcefully and quicker than ever before at a reduced operational cost.

Smart Cities Services. Petrolo, Loscri, and Mitton (2017), in their study about cloud computing of things as a driver towards a standard smart city architecture, represented smart city as one of the most promising and prominent but challenging Internet of Things (IoT) applications. According to Petrolo et al., Smart City can be defined as a concept of technological development that arises from the need to provide intelligent and enhanced applications to develop a better future for urban centers. There are studies identified that current cities are being developed, more populated than ever before, crowded with vehicles, become larger, and therefore the traffic monitoring, including surveillance is becoming a problem (Sun, Song, Jara, & Bie, 2016). Therefore, cloud computing is relied on as the solution to Smart Cities challenges, and this is one more area where cloud computing proved very successful (Krämer & Senner, 2015; Lan, Jiang, Fan, Yu, & Zhang, 2016). Moreover, based on a study of Pouryazdan, Kantarci, Soyata, and Song (2016), the Smart City features' big data such as the traffic control monitoring, signals of crowdsensing, security monitoring, and suspicious motions detections through geospatial ecosystems hold an incomparable catalog of challenges. Smart City bigdata requires specific transactional velocity and an enormous volume of geospatial data that can be a high barrier to successfully leveraging the ecosystem. For clarification, an urban traffic ecosystem feeds the geospatial center with refreshed near real-time data traffic, and these data rely heavily on processed information observed by cameras and other sensing detection mechanisms. Cloud computing data services such as BigData, BigTable, and MapReduce are the unique solutions to smart urban traffic control and monitoring from both perspectives of data processing power and storage. Cloud computing is the exclusive podium, capable of providing high capacity resources to support such a rapid change in information delivery and consumption (Maitrey & Jha, 2015). Yannuzzi et al. (2017), in his research about IoT and big data, illustrated that cloud computing was developed from a narrow technical field of application service deployment to solve bigger problems in the realms of smart homes and smart cities. Yannuzzi et al. (2017) recognized the standardized architecture, communication infrastructure, and cloud technologies to be able to provide intelligent feedbacks with high capacity communication within the digital convergence ecosystem.

In summary, smart homes and cities cannot flourish without high capacity and highspeed data fusion and data mining. In other words, the future urban quotidian life development will be negatively impacted without cloud computing. Many studies agreed within their findings that managing, processing, and blending mass flow of real-time information will only be accomplished through sophisticated and robust information systems architectures (Huang, Qie, Liu, Li, & Weng, 2015; Maitrey & Jha, 2015). Therefore, cloud computing technologies are a solid foundation to consolidate the physical infrastructure as well as to streamline service delivery platforms.

Energy consumption saving. The evolution of the IT hardware and software industry and the production of intelligent software and information processing to increase business efficiency heavily contributed to the growth of complex, data-intensive applications. Such development in IT industry required an indirect expansion of large data centers that caused massive energy demand and consumption for a continuous 24/7 business service availability. Hence, the increase in energy consumption is a serious global problem (Jagroep, van der Werf, Brinkkemper, Blom, & van Vliet, 2017; Kaur & Chana, 2015). The high competence of resource management, and the shared pooled resources mechanism associated with cloud computing services contributed to lowering energy consumption in the cloud center. Therefore, cloud customers who adopted CCS are plucking-out their data centers and hence reduce if not eliminate energy expenses to no return (Hameed et al., 2016). Kaur and Chana (2015) said that after cloud service adoption, organizations would follow a sound strategy to eliminate the data center that would lead to efficient use of energy. Moreover, there is not dedicated and generic research of study of universal consensus as to whether IT in-house data center is less energy efficient than cloud computing. However, analytically the cloud mechanism energy saving is explained and is two folds: (1) Adopters would be allowed to reduce or remove their inhouse data centers hence reduce or eliminate energy consumption. (2) The cloud infrastructure architecture and dynamic resource sharing management is an efficient resource management and hence, an optimization factor of energy consumption.

Therefore, cloud computing from a design and operational management would reduce energy consumption per unit of work and reduce cloud-client operational costs (Bui, Yoon, Huh, Jun, & Lee, 2017).

Large flexibility of service offering. The cloud companies are being numbered, such as Microsoft Azure, Amazon AWS, Amazon EC2, IBM, Google, SAP SE, and Oracle Corporation (Serrano et al., 2015). Within the cloud computing industry, many battles for a dominant market share that is growing the competition between cloud providers and key leaders of the industry, and which leads to the development of new pricing schemes (Mitropoulou, Filiopoulou, Michalakelis, & Nikolaidou, 2016). However, the cloud industry represents an extensive catalog of choice to look after the cheapest hosting provider that is contingent on the customers' specific needs. Such pragmatic algorithmic cost computation made the pricing methodology for cloud services a multidimensional function that has been shaped by the service's characteristics (Mazrekaj, Shabani, & Sejdiu, 2016); The IT cloud resources consumption-based pricing is elusive to how an ecosystem cloud solution integration is designed, implemented, and operated. Cloud services vendors use a variety of pricing mechanisms, including (1) usage-based fixed pricing, (2) usage-based dynamic pricing, (3) subscription-based pricing, (4) reserved services contracts with a combination of usage-based fixed pricing and up-front fees, (5) and auction-based pricing (Chekired et al., 2018; Soni & Hasan, 2017).

Moreover, the tiered pricing methodology that offers access to a set of computing resources that can be utilized as a pay-as-you-go model provides customers for adapting their consumption of cloud resources as per business need rather on forecasts (Ma, 2016; Mazrekaj et al., 2016). Amazon AWS (2018) provides an excellent example of CCS offers of the current market industry with competitive products of tiered pricing methodology of Pay-as-you-go, Pay-less-by-using-more, and Save-when-you-reserve approaches for over 100 cloud services. Microsoft Azure, Amazon Web Services (AWS), Google Cloud Platform, and many others are secure cloud services platforms. These CSP big players follow similar approaches of pricing to offer compute power, database storage, content delivery, and other functionality to help businesses scale and grow. A customer, through online web facilities such as AWS, can launch as many or as few virtual servers as needed, configure security and networking, manage storage, and select the right optimized pricing that fits his need (Microsoft Azure, 2018; Google Cloud, 2018). Finally, Tang and Liu (2015) explained the per-unit-based pricing allows customers to customize the needed computing resources while they pay for units of service. The subscription-based pricing refers to access computing resources for a recurring fee based on a specific period of time, usually a month, and hence the customer always has a pay-as-you-go or tiered hourly pricing options so that additional or extended services are immediately available as needed.

The TAM

The TAM was created in 1989 by Fred Davis, which was an extension of the Theory of Reasoned Action (TRA) presented by Icek Ajzen and Martin Fishbein in 1975.

The TRA was one of the persuading and influential models used by researchers in psychology (Ajzen & Fishbein, 1977). Ajzen and Fishbein (1977) associated with their theory one central construct of user's attitudes and beliefs to the adoption of technology. A few years later, Sheppard, Hartwick, and Warshaw (1988) trusted that Ajzen and Fischbein's model demonstrated a valid strength when was used in their defined restraints of studies, to analyze problems of choice: (a) either unclearly addressed, (b) or the intents of the participants of the study is based on assessments due to a gap in information. However, the theory stated that: The way an industry professional decides specific technology adoption or his positive attitude or behavior toward that technology could be determined based on his prior intention of the technology use (Ajzen & Fishbein, 1977). The Ajzen and Fishbein's model was used by researchers where: (a) The participants lack complete information for a conclusive decision, (b) The participants lack behavioral control during the study, and/or (c) other issues of choice that was unavailable during the study (Sheppard et al., 1988). Therefore, TAM is used by researchers as it allows information gathering with free influence on results by using PU and PEoU variables. TAM is a theory that helps to evaluate the technology ecosystem's influence on user characteristics acceptance (Davis, 1989; Wixom & Todd, 2005). Many researchers used TAM in their studies, and it helped to examine as a thorough tool to explain in-depth the adoption of IT (Davis, 1989; Davis et al., 1989). In TAM, there is a common relationship between the constructs predicted use, PU, and PEoU. In the research study of Bogart and Wichadee (2015), it has been shown that PU and user's behavior had a positive influence concerning the user intent of use of the “LINE” mobile App; hence, such result of the study is in full alignment with Davis’ reasons for TAM. TAM includes two key constructs to address user beliefs that characteristically influence the user attitude and his intention to use technology: the PEoU and PU of a technology.

Major Theoretical Models

Several theories had commonly been considered for literature analysis on technology adoption. These theories evidenced importance to be further used for theoretical foundation and detailed analysis for technology adoption studies. Such influential theories include the Technology Acceptance Model (TAM), the Extended Technology Acceptance Model (TAM2), the Theory of Planned Behavior (TPB), the Theory of Reasoned Action (TRA), The Diffusion of Innovations (DOI) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Fishbein & Ajzen, 1981; Venkatesh, Morris, Davis, & Davis, 2003; Rogers, 1996). To reach a good understanding of the settings surrounding the needs that drove TAM’s evolution, I would present a brief of theoretical models that forgone TAM manifestation. This vivid presentation of TAM historical development is important, especially that IT, through cloud computing permeated most aspects of human life, raising an imperative need to cognize why a specific technology is rejected or accepted (Marangunic & Granic, 2015). TRA had been structurally advanced to predict and understand human behavior. TRA, being a theory of behavioral predictions, evaluated behavioral intentions of individuals rather than their attitudes of intentions.

Moreover, the theory can imply actual behaviors that could be determined based on previous intentions (Leicht, Chtourou, & Youssef, 2018). TPB had been framed to resolve the limitations of TRA, to enhance the prediction of the intention of individuals engaged in technology adoption behavior in a particular place and particular time (Morten, Gatersleben, & Jessop, 2018). Therefore, Fred Davis modified these two theories, TRA and TPB, and originated the TAM, which aims to predict the acceptance and rejection of modern technology.

The TRA

The TRA helps to explain the behaviors originating due to individuals' perceptions. Social Psychology provided a framework of understanding how TRA exhibits individual behaviors based on specific inputs (Davis et al., 1989; Fishbein & Ajzen, 1981). These behavioral inputs originate from two major initiatives, according to Fishbein and Ajzen (1981): (1) the individual beliefs and perceptive evaluation of the facts, and (2) the normative motivation to comply with the new environment, as is typically reflected in Figure 5.

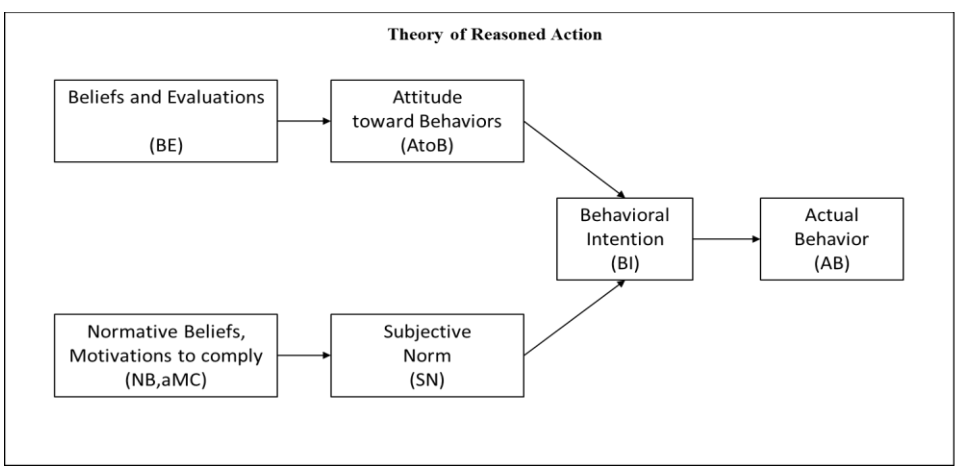


Figure 5. Constructs of TRA. Reprinted from *Davis et al., 1989, p. 985; Ajzen & Fishbein, 1977, p. 302*.

The BE influences the individual's AtoB, which stimulates the BI of that same individual. The normative motivation to comply (MC) influences the SN of the individual, which in turn inspires the BI. The model of Figure 5 depicts that The BI stimulates the actual behavior (AB) of the individual (Davis et al., 1989). The beliefs are the individual's evaluation of the facts that are causing to perform a target behavior, which will result in some consequences. These assessments refer to potential computed responses to the consequences of choosing target behavior (Fishbein & Ajzen, 1981). An individual's AtoB is strong-minded by the beliefs about the effects of substituting the behavior and the evaluation of those consequences. Therefore, the AtoB is recognized as the individual's positive or negative feelings about performing the target behavior (Fishbein & Ajzen, 1981). The perception of what is essential and what would be accepted or denied as intended behavior is part of the subjective norm (Fishbein & Ajzen, 1981). The subjective norm forms the first part of the BI or the measure of intention strength to perform a specific behavior (Fishbein & Ajzen, 1981).

The TRA as well hypothesizes that an individual SN is attributed to his normative beliefs and motivation to comply. In other words, the perceived expectations of an individual are associated with his motives to meet with those expectations (Fishbein & Ajzen, 1981). The SN forms the second part of the BI. However, and in the context of cloud computing, these SNs could be treated as the base from which IT managers and professionals formulate their decisions to test, accept, and then use the technology. This Subjective Norms base, based on which IT managers methodize their choice that could be influenced by the reasoned advice of trusted consultancies, IT solution architects, and professionals, as well as the credible literature and articles of technology magazines of announced successful experiences and implementations of technology.

TRA helped in many research studies to analyze behavioral intentions (Arpaci, 2017; Olubunmi Odewumi, Bamigboye, & Olusesan, 2017). TRA may aid in assessing behaviors exhibited by IT professionals while making decisions about cloud-computing adoption. Ajzen (1991) maintains that the TRA is limited to a set of assessments with which the actions or behaviors are mandatory. Therefore, the cloud-computing intention of adoption may fall in-within this realm in case IT managers are asked to evaluate and make decisions about adopting or not adopting the technology. Hence, TRA can provide aid to examine the individual decision-making behavior based on perception, and informs TAM. However, in such case, the TAM will model a refinement type of framework that aims more for technology acceptance and intention of adoption analysis (Oliveira, Alhinho, Rita, & Dhillon, 2017; Pornsakulvanich, 2017).

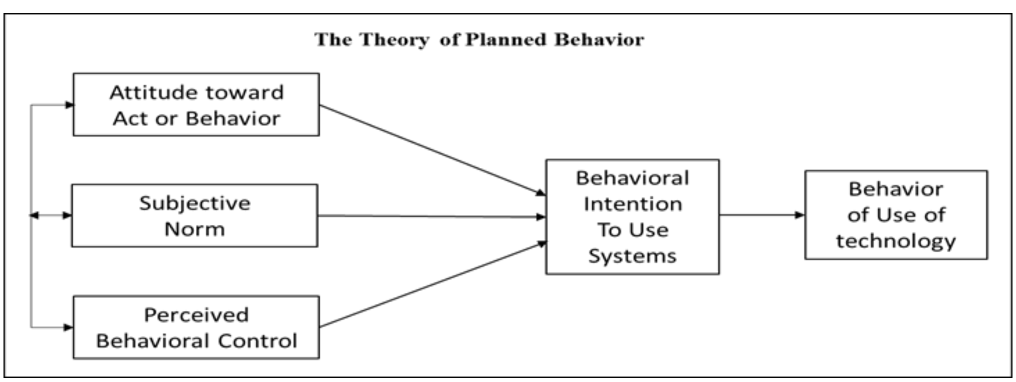


Figure 6. Constructs of TPB. Reprinted from *Ajzen (1991, p. 180).*

The TPB

The TPB is understood as being a fundamental improvement to the TRA. The TPB upholds what TRA hypothesized concerning the individual behavior resulting from his attitudes and behavioral intentions. However, TPB additionally incorporates some modifications that allow applying better accuracy and reliability to analyze and understand an individual's views and to predict his hesitating, planned, and resulting in actual behavior (Ajzen, 1991). The TPB postulates that individuals' behaviors are determined by specific intentions where behavioral intentions are the main parameters of the individuals' attitudes toward such behavior. The TBP postulation is understood as being the subjective norms surrounding the behavior performance that explains the individuals' perception of the ease of the behavior execution.

The TPB had found large scopes of studies, as being used in several fields and industries, and many applications (Masters, Morrison, Querna, Casey, & Beadnell, 2017). TPB became widely used in the field of behavioral and psychological research and evaluation studies (Li et al., 2017; Masters et al., 2017; Yahlali, Garcia, Díaz, Soriano, & Fernandes, 2017). Ajzen (1992) used the TPB in many of his researches, such as the one related to the applicability of TPB to Leisure Choice. What makes the TPB more acceptable than its predecessor, the TRA, is the higher cognizant ability of the factors that are out of the individual control. The predictability of intentions and behavior is higher than TRA, or other prior theories on predicting and understanding human behavior

(Ajzen, 2002).

The DOI

I sought to concisely explore DOI motif, as a theory, as someone may find a great conceptual similarity between DOI and TAM (Hua & Haughton, 2009). I thought this session would shed more understanding in-depth to the flow of user perception toward behavioral intention into the final intentional use of technology. Several types of research' theoretical framework relied on a combined architectural design of DOI and TAM (Alqatan, Noor, Man, & Mohemad, 2017; Mizanur & Sloan, 2017; Sabi, Uzoka, Langmia, & Njeh, 2016).

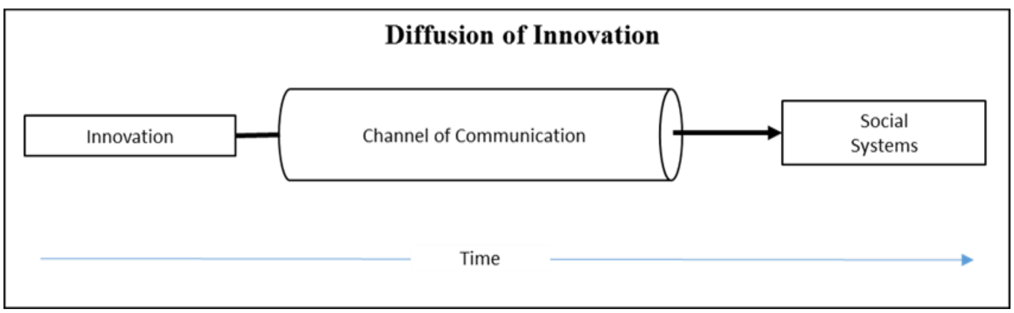


Figure 7. The diffusion innovation theory framework. Reprinted from *Rogers (1996)*.

The DOI is another widely used theory. DOI explains the factors of influence of the decisions to adopt and use new technology. Framed by Rogers (1996, 2004), the DOI theory was used in many various studies to analyze the potential factors that levied technology adoption, and the motives behind new technologies gaining acceptance and proliferation (Balas & Chapman, 2018; Dorr, Cohen, & Adler-Milstein, 2018; Rogers, 1996; Xu, Thong, & Tam, 2017). As shown in Figure 7, Rogers (1996, 2004) identified that diffusion is the process through which an innovation is communicated via channels overtime to the members of a targeted social system.

Rogers (1996, 2004) said that in a specific social system, a decision is made based on three ways. Rogers suggested that individuals make their decisions based on three scenarios: (1) Optional; where individuals made their decision in the social system by themselves. (2) Collective; where all individuals in the social system make the decision. (3) Authority, where few individuals decide for the social system as a whole. Rogers identified the mechanism of DOI by revealing five stages of flow for innovation-decision of adoption of use:

Knowledge. The individuals can expose a certain level of interpretation of the innovative technology as being a new novelty. However, they do not show any interest or get stimulated to at least test it or ask more about it, and that due to the lack of clear informative communication or good knowledge sharing about the benefits and needs of the innovation.

Persuasion. The individuals are showing interest in the innovation, and they proceed to spend time and effort seeking to know more by collecting detailed information about the change.

Decision. The individuals proceed effortfully seeking in-depth knowledge by analyzing the positives and the negatives of the innovation. At a specific level of knowledge satisfaction, an individual will be able to decide whether to accept or to reject the innovation.

Implementation. The individuals who are about to decide adoption of the innovation, take some efforts to recognize the requirements and other dependencies of the innovation. Hence, those individuals will dedicate more time collecting more comprehensive information to optimize the usefulness of the new technology.

Confirmation. The individuals who, after the implementation phase have concluded implementation feasibility with a sustainable scenario of the optimized and beneficial use of the innovation, do conform to final decision making by taking a further step to close a deal and to adopt the use of the new technology with full potential. Therefore, and as presented in Figure 7 below, the DOI theory perceives innovations spread among social groups through defined channels of communication over time. The interested individuals possess the technology at various degrees of willingness to adopt innovations. It is observed that portions of the social system fostering a new change are approximately normally distributed over time (Rogers, 1996; Rogers, 2004). The Figure 7, breaks this normal distribution driving specific segregation of individuals into five categories: (a) innovators, (b) early adopters, (c) early majority, (d) late majority, (e) laggards.

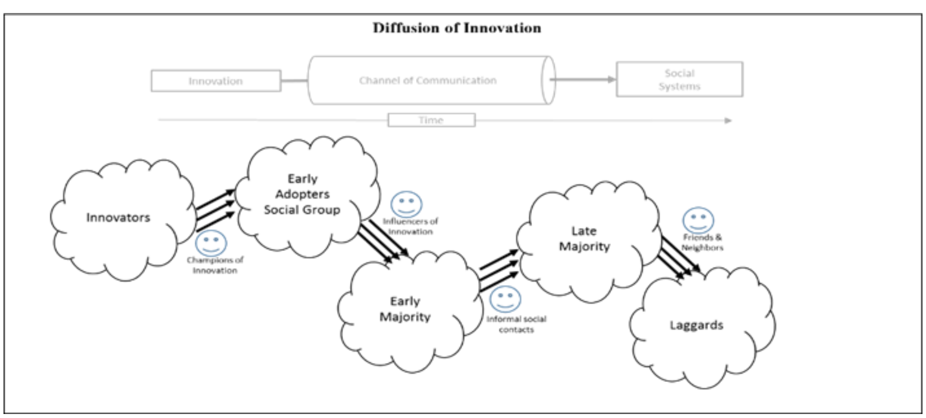


Figure 7bis. DOI flow among the groups of adopters, as explained by Rogers (2004).

The members of each of the five categories retain unique characteristics laying behind the innovation adoption decision making: (a) the innovators are the venturesome individuals of the social group, they are educated, sociable and interconnected among multiple info sources, (b) The early adopters generally are the social leaders, who usually seek to be privileged among their communities, seek channels to remain very popular and highly reputed, and are as well-educated and socially interconnected, (c) The early majority group is deliberate, very cautious in taking a decision and rely much on trusted informal social contacts, (d) The late majority are the skeptical individuals who doubt anything new presented. They always prefer to rely on the traditional mechanism and avoid changes; this group is characterized by being lower than previous groups in socio-economic interactions, (e) The laggards are the individuals influenced by their neighbors and their friends, who generally are considered their trustful main info sources, this category of individuals in the social system usually fear any loss and avoid bad-debt investment.

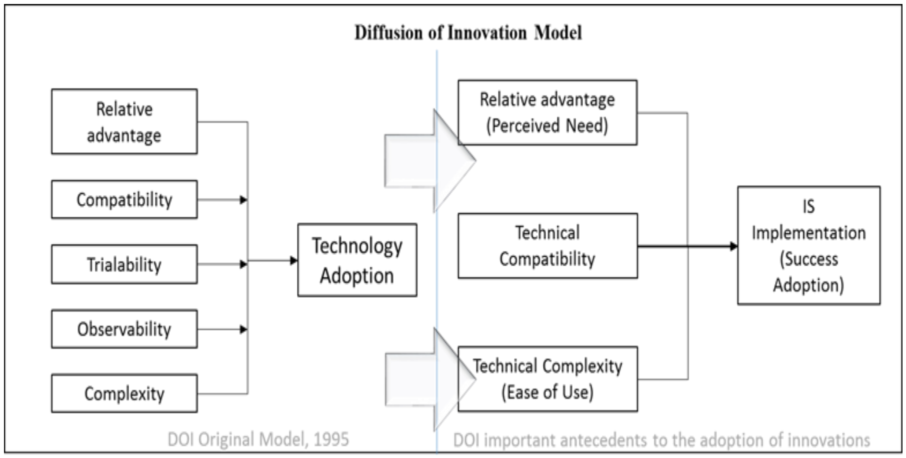


Figure 8. DOI framework evolution. Reprinted from *Rogers (1996, p. 283)*.

The innovation dissemination ratio is measurable and can be presented based on a cumulative percent S curve to represent the rate of adoption of the innovation within the population (Rogers, 1996; Rogers, 2004). According to Rogers, and as presented in Figure 8, the ratio of adoption of innovations is impacted by five factors: relative advantage, compatibility, trialability, observability, and complexity. The first four factors are generally positively correlated with the ratio of adoption, while the last element, which is complexity, is generally negatively correlated with the ratio of adoption. Moore and Benbasat (1991), in his study of IS context, had expanded the DOI model by generating eight factors which are: voluntariness, relative advantage, compatibility, image, ease of use, result demonstrability, visibility, and trialability proving the impact of all presented constructs over the intention of adoption of IT. However, and since the early applications of DOI to IS research, the theory has been applied and adapted in numerous ways. Research has, yet, consistently found that technical compatibility, technical complexity, and relative advantage (perceived need) are important antecedents to the adoption of innovations (Bradford & Florin, 2003; de Vries, Tummers, & Bekkers, 2018; Mannan, Nordin, & Rafik-Galea, 2017) leading to the generalized model presented in Figure 8.

The UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT), is widely used in scholar studies to analyze factors of influence of technologies intention of adoption and actual use (Moryson & Moeser, 2016; Alharbi, 2017; Sabi et al., 2016; Ooi, Lee, Tan, Hew, T. S., & Hew, J. J., 2018; Sharma et al., 2016). Even with TAM and its extension model TAM2, that ability to predict technology adoption rate is limited up to 50% of the cases (Oye, Ab-Iahad, & Ab-Rahim, 2014; Venkatesh & Davis, 2000). Such limitation primed researchers to find a better model that would enhance the prediction of technology adoption. Venkatesh et al. (2003) hosted the UTAUT with the ultimate expectation of reaching a stage of predicting technology adoption better than TAM and TAM2.

Venkatesh et al. (2003) had evaluated eight pre-existing theoretical models, precisely were; the Theory of Reasoned Action (TRA), the technology acceptance model (TAM), the Motivational Model (MM), the Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), Diffusion of Innovation Theory (DoI) and finally the Social Cognitive Theory (SCT). Out of all the examined variables, only four of them were deemed to be the most influencing factors on foreseeing the intention of users to use technology. UTAUT aims to explain user intentions to adopt and use information technology innovation and subsequently allow to analyze the behavior of technology use.

UTAUT, as shown in Figure 9, grips four fundamental constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions; that which are used as direct determinants of usage intention and user behavior (Venkatesh et al., 2003). The external variables gender, age, experience, and voluntariness of use are postulated as external influencing variables to control the impact of the four critical constructs on usage intention and behavior (Venkatesh et al., 2003). Subsequent validation of UTAUT in a longitudinal study found it to account for some technologies offering direct services to end-users, 70% of the variance in usage intention (Venkatesh et al., 2003).

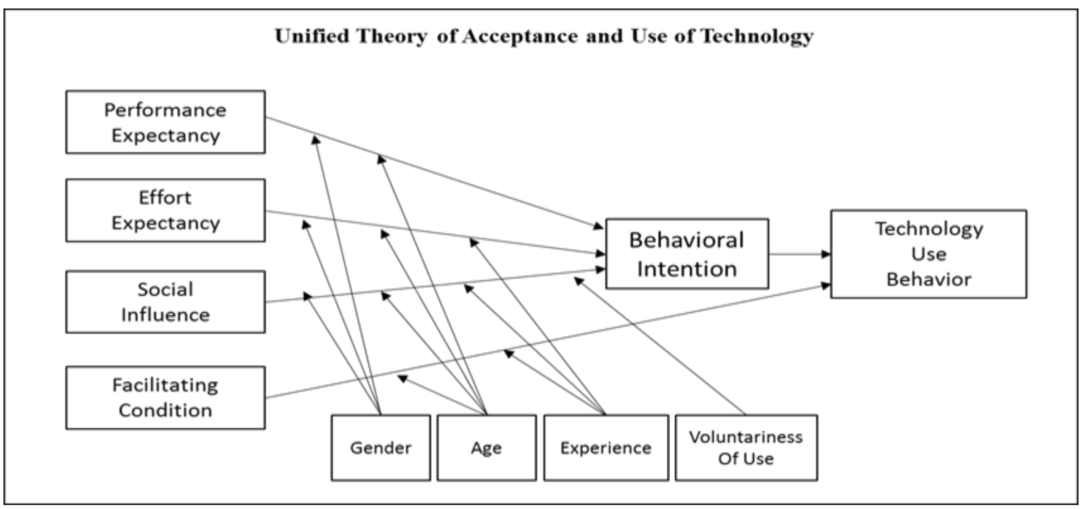


Figure 9. Constructs of UTAUT. Reprinted from *Venkatesh et al., 2003, p. 450*.

The UTAUT evaluated several representations of human behavioral intention based on four essential constructs that would accurately predict the intention to use technology. Several studies modified UTAUT by extending the framework to predict the intention of adoption of technology in various environments and to show that it applies to different genders, cultures, and IT competencies (Bhatiasevi, 2016; Maillet, Mathieu, & Sicotte, 2015). As an example of theory manipulation of use; Maillet, Mathieu, and Sicotte (2015) identified end-user acceptance and satisfaction, which are two more variables and key factors of influence to implement successful technology such as healthcare patient electronic records. Venkatesh, Thong, and Xu (2012) introduced their UTAUT2 of study, a modified model of UTAUT to study more accurately the consumer acceptance and use of technology. By introducing and examining specific contexts like consumer intention, the study helped to identify new constructs that can serve as accurate predictors of intention. Ain, Kaur, and Waheed (2015) found that UTAUT did not consider students perceived value regarding learning and associated fun and pleasure. To bridge this gap, the authors used UTAUT2 and added learning value in the place of the price while keeping the hedonic motivation and experience and habit constructs.

In a comprehensive review of UTAUT of Williams, Rana, and Dwivedi (2015), they identified limitations of UTAUT observed across other studies. These limitations included a key fact that most of the studies focused on the same environmental analysis concerning culture, country, community, agency, and age group. According to Williams, Rana, and Dwivedi (2015), this is a key constraint that limits the generalization ability of the results.

The TAM

The TAM has been one of the IS theories most commonly adopted models to analyze and understand the adoption of information technology (Durodolu, 2016; Lai, 2017; Wu & Chen, 2017). TAM hypothesizes two main constructs of PU and PEoU that shown through several research findings as being most essential attributes in explaining adoption of new technology systems (Campbell et al., 2017; Davis, 1989; Holden & Karsh, 2010; Tarhini, A., Hone, Liu, & Tarhini, T., 2017; Xu, Thong, & Tam, 2017). According to Davis (1989), the PU is the individual belief measuring factor of what level of enhancement would appear on one’s job, once a new particular system is in use. The PEoU is the measuring indicator of an individual who believes that using a specific system would be effortless and more comfortable.

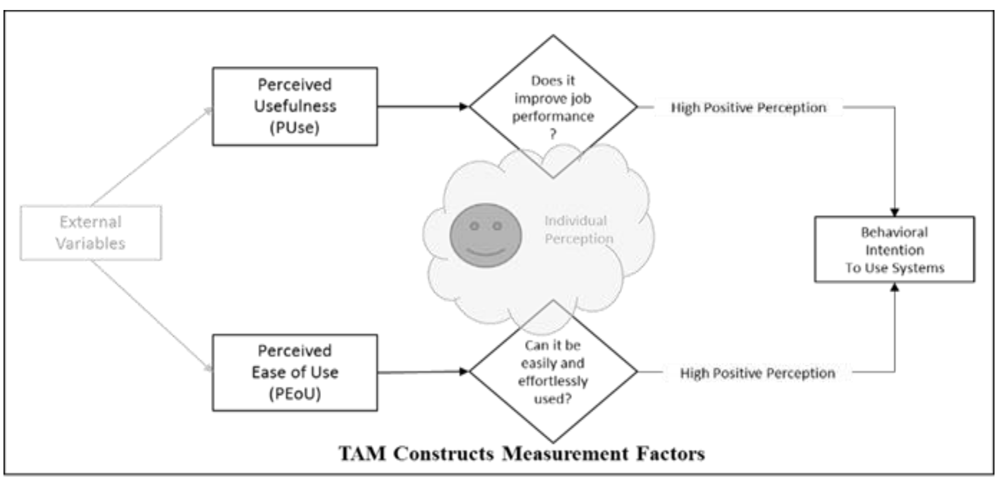


Figure 10. PU and PEoU constructs of TAM.

In Figure 10, PU of a specific technology is used to explain the level of perception to an individual for which adopting the technology can improve job performance, while, PEoU refers to the degree by which using a particular technology is perceived to be effortless (Davis, 1989). Moreover, there is a relationship between PU and PEoU; as Venkatesh and Davis (2000) explained, the Usefulness of technology may be prejudiced by its ease of use because the easier it is using technology, the use the technology is. Holden and Karsh (2010) admitted that TAM is significantly important for the behavioral intention of the adoption of technology, but in some circumstances, it is suffocated with some limitations. Tarhini et al. (2017), to overcome possible constraints of TAM in developing countries, extended TAM by including subjective norms, and quality of work-life as additional constructs with some cultural variables as moderators. Many other researchers suggested a TAM extended model by adding additional external variables related to environment dynamics, human behaviors as well as social change processes (Campbell et al., 2017; Xu, Thong, & Tam, 2017).

Although TAM is specific to information technology acceptance and is supported considerably by empirical studies, it has been criticized for its parsimony (Taherdoost, 2018; Venkatesh & Davis, 2000). TAM and extended TAM based analysis aided to reveal that external constructs such as quality, security, and satisfaction significantly influence the intention to adopt technology and, consequently, the acceptance of use. The TAM and its extended models, can help gauge and predict how technology users may respond to the solution technology as a service implementation. Many studies based on TAM and extended models of it proved that TAM could be used as a foundation for technology service providers to develop strategies to encourage people to use new technologies and increase the usage and acceptance rate. Holden and Karsh (2010) proved that TAM predicts large portions of the use or acceptance of IT health services and hence recommended that the theory may benefit more if it is enhanced from several additions of constructs and modifications. In addition to the PU and PEoU, other theories' constructs in marketing, human behavior, psychology, business management, and economics had been added and included in the TAM. Venkatesh and Davis (2000), as shown in Figure 11, added an external box of influencing variables as a key construct impacting the intention to use technology by influencing both PU and PEoU.

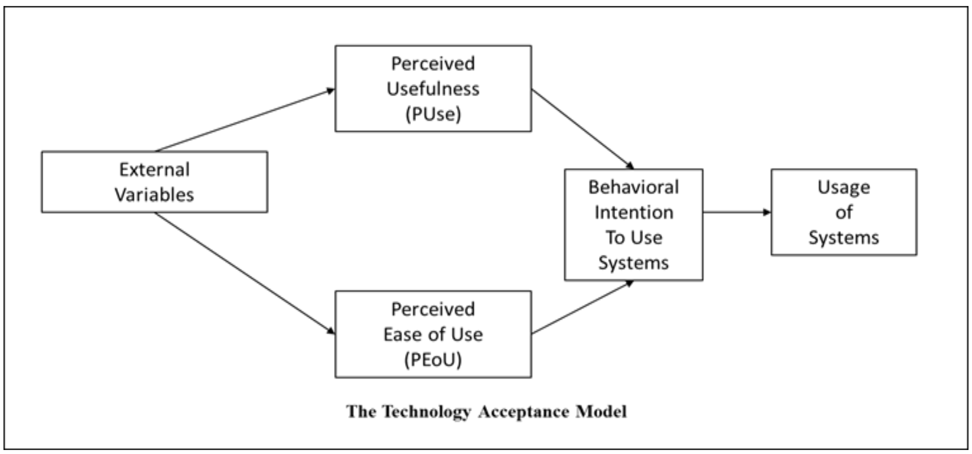


Figure 11. TAM framework structure. Reprinted from *Davis et al., 1989, p. 985*.

Therefore, the external variables of TAM such as environmental dynamics, public and governmental regulations, individual characteristics, culture, and education, or business managerial support can produce significant effects on individuals' behavior and consequently on both PU and PEoU factors of Davis, which had been used as foremost composers of the original TAM model.

In this original TAM of Figure 11, Davis made two changes to TRA and TRB models; he dropped the subjective norm construct and manipulated by adding two more constructs the PU and the PEoU (Marangunic & Granic, 2015). Further after, a later study, an extension of TAM was proposed to embrace more factors that include subjective norm and help increase the identification rate of the factors that influence PU (Venkatesh & Davis, 2000). Figure 12 shows the proposed TAM 2 extension reflecting the set of additional variables that may affect PU.

The TAM2 figure demonstrates that several factors influencing PU had been suggested; The subjective norm, image, and job relevance, output quality, and result demonstrability. Venkatesh and Davis (2000) examined each of these to see how they affect the PU of a technology. In the TAM model, Venkatesh was able to reliably elucidate an approximate 40% prediction rate of usage intentions and behavior. However, with the TAM2 model, Venkatesh was able to account for 34% to 52% in usage intentions.

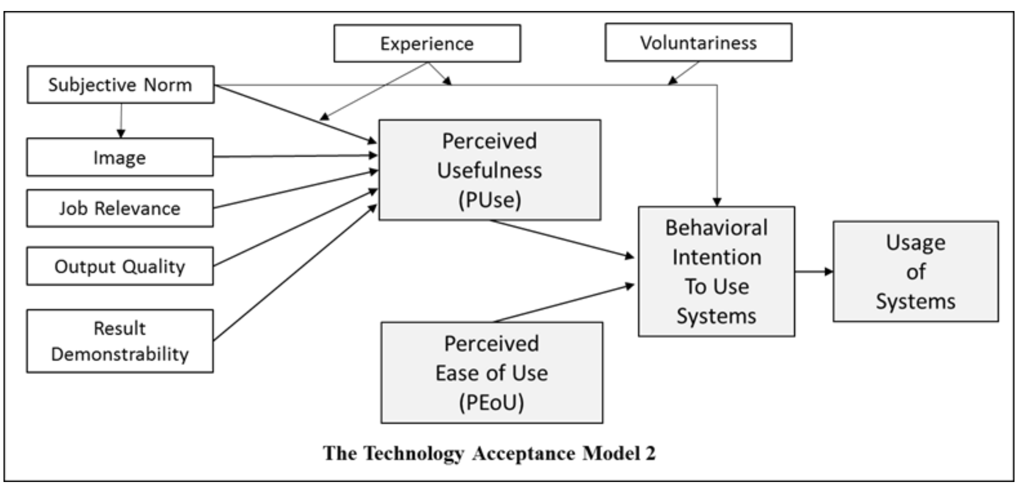


Figure 12. Constructs of the TAM2. Reprinted from *Venkatesh & Davis, 2000, p. 120*.

As presented previously in this literature review, that several theories were established and being developed through the time, and all are helpful for IT problems research and analysis: They include, but not limited to, the DOI, TRA, TPB, UTAUT, TAM, and TAM2. Each of the theories is a bastion with strength and limitations. Despite these theories complement by nature and design each other, one may fit a study better than others depending on the need and limitations. The TAM, in my view, was most suitable for my study as it allows prediction of technology users' behavior by considering the extension of external variables. Theoretical design similarity of TAM was suggested by several previous studies of IT in internet Banking, mobile banking and internet healthcare by Ukpabi and Karjaluoto (2017) and supported by too many credible researches such as Fawzy and Esawai (2017), Wann-Yih and Ching-Ching (2015), and Razmak and Bélanger (2018).

In addition to this, the validity of the theory has also been tested and was found to be impressive in technology adoption studies such as internet, cloud computing, eBanking, eCommerce, eLearning, and eHealth-care, as well as cloud computing as an industrial source of IT services (Chaouali, Souiden, & Ladhari, 2017; Conzales-Martines, Bote-Lorenzo, Comez-Sanchez, & Cano-Para, 2017; Hassan, Iqbal, A., & Iqbal, Z., 2018; Ooi et al., 2018; Rani et al., 2015). The TAM's central variables of PEoU and PU, has been adjudged as important determinants for IT users intentional, behavioral, and attitudinal acceptance and performance and is one of the most widely and practically used theoretical models in the IT and IS industries such as cloud computing.

The TAM is also one of the most influential and commonly adopted theories for describing an individual's acceptance of information systems (Durodolu, 2016). Shim, Lee, and Kim (2018) observed certain beliefs of both PU and PEoU that controlled direct relations to the attitudes determining the use of technology. PU is seen by Zhou and Teo (2017) as well as Teo (2018) as a personal vision indicating that some application systems that are positively impacting productivity performance increase job performance in organizations. The PU positive impact on job performance is also defined as performance expectancy. Durodolu (2016) perceived that PEoU is anchored on the conviction of being a presentation of the effortless and hassle-free indicator to procure a particular skill identified as effort expectancy. In the opinion of Zhou and Teo (2017), Teo (2018), and Durodolu (2016), the TAM anticipated that attitudes have a specific constructive impact on the mindset of individuals that gears human efforts towards the use of technology.

PU. Access to information has shown an improvement in human competence through the era of the development of IT and cloud computing (Muda et al., 2017; Nieves & Quintana, 2018). Mohammadi, Abrizah, and Nazari (2017) suggested through their study of information quality that the attainment to an adequate capacity to access reliable information is affected by the reluctance of users to admit using available techniques. PU, and according to Davis (1989), is the degree to which an individual believes in a particular used technology that would improve job performance and enhance productivity. Davis (1989) explained that this perception is fastened based on some considerations that the access to reliable information capacity developed will strengthen human performance. Davis (1989) believes that people are by nature, motivated for better productivity and performance by enhancing the work environment. The environmental improvement is subject to sophisticated tools of trade, salary raises, promotions, bonuses, and other moral rewards such as recognition and retention plans. The TAM can provide significant value to research because, in previous studies, it demonstrated its capability to improve analysis concerning users' job performance. PU has been proven in various studies to be a crucial factor in technology adoption (Wu & Chen, 2017).

PEoU. Davis (1989) stated that PEoU is the level of a degree to which a technology user considers that, to start using an acquainted system is effortless and hassle-free. The PEoU is the perception of moving into freedom from any complex tasking and any other trouble. The conclusion is that an application, that is perceived by users to be easier for use, would be accepted and easily utilized by most of the people. Wu and Chen (2017) in their study of the seamless acquisition of new technology, revealed that PEoU signifies the level of a degree where an individual start accepting the use of an offered technology. Abdullah, Ward, and Ahmed (2016) confirmed that user acceptance behavior starts positively changing as soon as he intuitively experiences the new technology as being uncomplicated and unproblematic. Hence, the system characteristics help increase the level of acceptance of the IT user as being led by the ease of use of technology and system usage. Raut, Priyadarshinee, Gardas, and Jha (2018), in their study of cloud computing, enumerated certain factors that may influence the ease of use of IT resources such as technical characteristics of information resources, relative advantages, smooth experience, business integration, and support, etc.

External variables. Gangwar et al. (2015), in his study, confirmed that the factors relative advantage, complexity, compatibility, skill and competence, training, education, and management support of the Technology-organization-environment framework (TOE); are external variables influential to technology adoption of cloud computing that has been used along with the TAM. Gangwar et al. (2015), confirmed that their study had identified the mentioned variables as being key factors for affecting cloud computing adoption using PEoU and PU as mediating variables. Gangwar et al. (2015) added that competitive pressure and trading partners support found affecting cloud computing intentions of adoption; the model of study allowed him to explain that these two variables might affect cloud adoption at a ratio of 62%. Gangwar et al. (2015) recommended that more external variables, which are in direct relationship with PEoU and PU, are worth further studies to understand the impact on CCS diffusion among organizations. A more recent study of Palos-Sanchez et al. (2017), with external variables such as top management support, training, communication, organization size, and technological complexity in Andalusia of Spain, that data was compiled from 150 companies; the results reflected those variables as being critical factors impacting PEoU and PUse of TAM. Gangwar et al. (2015) and Palos-Sanchez et al. (2017) confirmed a robust conceptual generalization of study of TAM in their findings.

External Variables of the Study

In this study, I tallied the PeS, PeP, PeN, and PeC to be used as the external variables of TAM to investigate and test their relationship of influence on PEoU and PU. Senarathna et al. (2016), in his study concerning cloud adoption by Australian SMEs, found that privacy and security factors do impact the intention of cloud adoption; however, they are not the most critical concern for Australian SMEs. Lee and Shin (2018), in their analysis of financial technology systems (Fintech) challenges, exposed security and privacy as being the most critical factors of mistrust of the consumer. Lee and Shin revealed in their study that Fintech applications require storing crucial information on mobile devices that frequently get lost or stolen, and that security of mobile devices often compromised by payment applications such as Google Wallet and MasterCard PayPass. Lee and Shin (2018) recommended that Fintech companies, and through their cloud ecosystems, need to develop appropriate measures to protect sensitive consumer data from unauthorized access. Stergiou et al. (2018), in a combined study about CCS and IoT security and privacy, revealed that cloud computing as being an evolving paradigm with tremendous momentum, its architectural aspects exacerbate security and privacy challenges. Stergiou et al. confirmed that security is one of the major issues which reduces the growth of cloud computing, and complications with data privacy and data protection continue to plague the market.

Prior Technology Adoption Research

Similar studies of cloud computing adoption had been applied in many developing countries such as Africa and the Middle East. Through those studies, researchers had examined some influential independent variables impacting cloud computing adoption. Sabi et al. (2016) said the DOI’s constructs of relative advantage, compatibility, trialability, observability, and complexity used as external variables with TAM is a convenient model allowing to measure and analyze the contextual, economic, and technological influence on behavioral intention of CCS adoption in Africa’s sub-Saharan universities. Mohammed, Ibrahim, and Ithnin (2016) said governments in developing countries are not ready to adopt e-government solutions due to the deficiency in resources, poor technology infrastructure, and lack in IT technical and administrative skills, in addition to the low level of education and literacy. Mohammed et al. proposed a model to explore the main factors influencing governments in developing countries to adopt cloud computing for e-government services provision relying on the constructs of DOI and TAM. Omotunde et al. (2015) found that security and privacy are key factors for SMEs to stay reluctant to adopt cloud computing. Sharma et al. (2016) showed that computer self-efficacy, PU, trust, PEoU, and job opportunity are the main factors affecting the intention of cloud adoption. Ramachandran and Chang (2016) and Ramachandra, Iftikhar, and Khan (2017) said security and privacy are constructs of significant impact on behavioral intention of CCS adoption. Too many other researchers based on extended TAM using constructs of other IS theories have dedicated studies, for Africa, Middle-East, and Far-East to analyze main factors such as security, internet connectivity, complexity, and job opportunity that most of them are found impacting CCS adoption (Al-Ruithe et al., 2017; Kirubakaramoorthi, Arivazhagan, & Helen, 2015; Senyo, Addae, & Boateng, 2018; Senyo, Effah, & Addae, 2016).

At the time of the research, works of literature on cloud computing in Afghanistan were limited if nonexistent. I found a few articles concerning the use of some specific services on the cloud. Matin et al. (2016), through their study concerning agriculture control service, a solution had been deployed on the cloud for Afghanistan, confirmed that the internet and computing infrastructure in Afghanistan is very minimal. However, they used the cloud computing platform of Google Earth Engine (GEE) to accomplish their work of study. Castiglione, Choo, Nappi, and Narducci (2017), in their study of designing secure data access and authentication in a cloud computing environment using Biometrics-as-a-Service (BaaS), proposed Afghanistan for such type of research. Kabiri and Wannous (2017) said e-education in Afghanistan if deployed, might help to increase the students' pass rate by 25%. However, during the test study, Kabiri and Wannous (2017) report mentioned service interruption due to latency and low performance in internet service, especially in Internet usage peak times.

Transition and Summary

Section 1 of the research presented the IT problem of cloud computing adoption in Afghanistan tackled by this study and introduced facts about the technology and the background of the problem. The section presented the purpose of the study, the IT problem statement, which both lead to the research question and to the hypothesis that was tested in further sections of the study. Furthermore, Section 1 presented additional information concerning the nature of the study and the significance of the study to IT and how the technology benefits could influence social change. Moreover, the literature review of the study concludes the section with an in-depth description of the TAM theoretical framework that was used in the study analysis and how it was applied to the problem described.

Section 2 reaffirmed the IT problem and provided deep and more imperative information about the research methodology that was selected for the analysis in this study. Section 2 provided further information on the role of the researcher, the target population, the sample selection, and the size sampling computation, the instrumentation and data collection methodology, data organization and analysis, and a final statement about reliability and validity of the study. Section 3 of the study presented a statistical analysis of the collected raw data, an overview of the findings that would come out of the collected data analysis, and it extended the application of the findings of the study into professional practices, its implications for social change, and recommendations for actions and further studies.

Section 2: The Project

Section 2 presents a detailed discussion of the project study. I discuss my direct involvement in the study as a researcher, analyst, and writer. I define the criteria for the eligibility of participants. I discuss the methods and research design I used for this study. Furthermore, I include an informational presentation on how I managed as a researcher and writer to maintain Walden's ethical boundaries. I abided by Walden University's Institutional Review Board (IRB) requirements and protected the participants based on IRB's application. Finally, I provide details on data collection for the study and analysis methodology and procedures, including issues of validity and reliability.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with IUoT. The target population was technology IT solution architects of SMEs in Afghanistan. The independent variables, namely, were PeS, PeP, PeC, PeN, PU, and PEoU, and the dependent variable was the IUoT of CCS. The study's findings may contribute to positive social change in reducing energy consumption and carbon dioxide emission once CCS adoption spreads out in developing countries.

Role of the Researcher

For this quantitative correlational study, my role as a researcher consisted of defining the research question and related hypotheses of the study, finalizing the literature review, collecting, organizing, and analyzing data, presenting findings, and proposing recommendations for future studies. In this research, my purpose was to (a) identify the hypotheses and research question, (b) finalize the theoretical framework design, (c) create survey questions for data collection, (d) apply appropriate statistical methodologies for trustworthiness without bias, (e) collate and analyze the results, and (f) confirm study findings with recommendations. According to Larson-Hall and Plonsky (2015), the main role of the researcher in any quantitative study is to collect, compile, and analyze the data to test the proposed hypotheses and subsequently answer the research question. My role in this study was to organize, manage, implement, and evaluate my research. I recruited participants and collected data for analysis. I used a valid survey instrument (VSI), which is an online questionnaire using SurveyMonkey, to investigate and examine the relationship between IT solution architects' perceptions of security, privacy, complexity, and connectedness and their intention to adopt and implement CCS.

I had been working as a CIO for more than 15 years and was involved with cloud computing services implementation for the last 3 years during the writing of this study. My background might result in experimenter bias because of my own experience in the IT industry and my views on the CCS topic of the study. The participants contributing to the study maybe were peers, colleagues, direct reports, or done business together might be affected to answer questions in a way they think I accept and like. Roberts and Allen (2015) said experimenter and social desirability biases could be mitigated through the use of anonymous data collection techniques. To ensure reliability, researchers should identify biases before data collection and organize their work to eliminate it (Vydiswaran, Zhai, Roth, & Pirolli, 2015). My perception of personal researcher bias in this could affect findings. Researcher biases include confirmation bias, question-order, leading questions and wording bias, sponsor bias, experimenter bias, and social desirability bias. Therefore, I planned appropriately to limit such unintentional researcher biases from happening. Vydiswaran et al. (2015) recommended that researchers continuously examine the evidence supporting or contradicting claims to alleviate biases. Krishnamurthy and Chetlapalli (2015) stated that biases could be mitigated by relying on arbitrary multistage cluster sampling time limit, which is the taking of samples in stages at different times, sampling that ensure a diversified representation of the population, and lucid syntheses of previous studies. I did not have any relationship with the participants in this study. The survey, which is an online set of questions in groups, was managed from a distance and consisted of anonymous questionnaires. According to Schwab-Reese, Hovdestad, Tonmyr, and Fluke (2018), quantitative survey questionnaires are usually designed to collect and analyze research data without direct interactions between participants of the study and researchers, either in person or remotely.

The Belmont Report requires that a researcher should abide by three main principles: (a) respect for persons, (b) beneficence, and (c) justice (U.S. Department of Health & Human Services [DHHS], 1979). I abided by the requisite ethical doctrines of IRB for research and disclosed my research status and objectives to participants. I studied the Belmont Report to understand the ethical beliefs and guidelines that were vital for the protection of human subjects as per the National Commission for the Protection of

Human Subjects of Biomedical and Behavioral Research. I strengthened my ethics of research knowledge by completing the National Institutes of Health (NIH) Protecting Human Research Participants training course and got my certification (Certification Number: 2394255; see Appendix B). To safeguards the ethical principle of respect for participants of the study as defined in the Belmont Report, researchers should ensure informed consent by presenting all essential information about the topic of study to participants, including data collection procedures. Clarke, Barnes, and Ross (2018) said a research survey might include elements of passive coercion and a lack of timely and appropriate information that influences the way some participants make decisions. These factors might disempower participants at the point of decision-making. A clear and structured informed consent is needed where participants are enabled to have control over decisions.

Moreover, researchers should ensure informed consent for the evaluation of risks that may incur due to their dual roles. My dual roles consist of being the sponsor of the research and an IT professional known to participants, which may influence them. Clarke et al. (2018) said a dual role is the cases when a researcher, due to his background and experience about the topic of study, being in contact with the participants might unintentionally influence, manipulate or teach the participant. I selected a reliably tested instrument, which is a set of questions in groups used in previous research of TAM (see appendix A). I used the instrument to analyze IT solution architects' intention of adoption of IT technology with slight modifications, to accommodate the external variables of

ETAM of the study, and avoided any direct contact with participants before the start of the study. In addition to that, I followed an anonymous process for data collection, and I stated clearly in the informed consent form that the information provided would be used solely for my doctoral study research and not for my role as a CIO.

Participants

The main selection criteria of participants for the eligibility to participate in the survey was determined by the quality knowledge of the individual suitable to the research questions. Meesariganda and Ishizaka (2017) said that the topic and the role of the population in the research might help to identify the requirements of eligibility for the participants filling out a survey. But from another perspective, Gumbi and Mnkandla (2015) said the lack of standardization among cloud computing users, making it challenging to define a unique perception between the viewpoints constituting basic cloud computing functionality. The main survey eligibility criteria of SMEs IT solution architects should have experience or at least deep awareness about different cloud computing concepts relating to their organization.

I used for the data collection of the study participants from the IT industry in the role of IT solution architect and expert with at least 5 years of experience. My participants of the study shall have basic knowledge of CCS and benefits in return. Hence, I targeted to contact IT solution architects that are employed for SMEs in Afghanistan's main cities such as Kabul, Mazar, and Herat. As such, I guaranteed a good level of awareness and knowledge about CCS pros and cons with participants who are handling IT infrastructure resources of their in-sourced data centers, manage and maintain applications, including user enterprise services. In addition to that, such participants of the study who are handling IT operation, quality setting, and related strategies of services expansion and upgrades, would provide accurate answers to my survey that stemmed from experiences that reflected the real challenges and need for a better IT environment.

I assumed participants of the study knew the benefits CCS would bring to their organizations. I believed participants were responsible for implementing and maintaining their owned data center components, including servers, data storages, cooling systems, fire extinguisher systems, and security monitoring systems. I believed as well participants were aware of expenses and costs to accommodate an operational setting of standards. Those participants have adopted or about to adopt CCS and were conceptually and technically aware of accessing remote cloud resources, and the concept of remote storage of data.

I obtained the endorsement of the IRB committee to contact the participants based on the Walden IRB. The IRB ensured my research adherence to the requirements and ethical rules of Belmont Report protocols. Without IRB, any access to participants was unauthorized and might expose the subjects of study and might root some undesirable consequences towards the researcher.

After the IRB approval was received, I initiated the communication with the participants. The Ministry of Commerce and Industry (MOCI) maintained a database of

SMEs operating in Afghanistan that included executives and departmental heads contact credentials. I filtered out the list of SMEs with the contact credentials of IT personnel to facilitate access to the potential participants, out of which I randomly selected participants to take the survey. To ensure the protection of the participants' identity, my survey of the study was anonymous, and the email invitation explained the research purpose and provided a hyperlink to the first page of the VSI, which presented the informed consent form. At the start of the survey, participants reviewed the consent form. They acknowledged their understanding by checking at the bottom of the informed consent page a checkbox to confirm the statement that says, "I have read the above information and agreed to participate in this study. I am at least 18 years of age…", after then, the participant was directed automatically to the survey questionnaire. However, providing the participants with informed consent and anonymity clause had protected human subjects' research as required by the Belmont report (Cross, Pickering, & Hickey, 2015; Roberts & Allen, 2015; Shoenbill, Song, Cobb, Drezner, & Mendonca, 2017). Therefore, I provided the participants of the study with the necessary information about my study and related survey to assure them that their information was completely anonymous. The eligibility criteria for participant to join the survey is: (a) being an IT operational and strategy senior, (b) being employee of SME registered at the MOCI at the time of the study, (c) being of at least 4 years of experience in IT, (d) being of at least 1 year of experience in IT solution architecture and design, (e) being aware of CCS.

Before I started the collection of data and based on random sampling, I followed a firm strategy to obtain the appropriate subjects that meet the eligibility criteria required for this study and to increase a good ratio of respondents. Singh and Wassenaar (2016) stated that to gain access to participants, it requires the approval of the gatekeepers, which facilitate access to participants targeted by a researcher. Therefore, I sent to IT departments' managers of the targeted SMEs, an email informing about the purpose of the survey to win their cooperation and internal leadership approval to facilitate reaching out to the potential participants for the study. Wallerstein, Duran, Oetzel, and Minkler (2017) specified that research participants have higher tendencies to agree on their contribution in a study if the research problem and question are relevant to their field of work or their future projects. Participants as well would agree to contribute to research if outcomes would help their organizational strategic policies. Based on the list of IT solution architects from MOCI, I sent the email invitation that will help to outline (see appendix E), the purpose of the study, and benefits participants might get if they contribute. Appendix E highlighted benefits include enhancements of participants' organizational CCS strategy, security challenges, and cost versus benefits returns.

Furthermore, to gain a successful contribution of participants in the survey, it was vital to building a good working relationship between participants of the study and the researcher. Green, Swailes, and Handley (2017) said participant integrity and openness to the study to disclose quality data is motivated by the relationship between the researcher and the participant. Hence, the working relationship between an action researcher and participants is integral to the quality of the research output. von Benzon and van Blerk

(2017) stated that the identification of appropriate participants and fortifying both parties' mutual benefits of returns to be part of the research project is one of the most important steps in establishing a working relationship. However, I planned to establish two-way communication to participants: one vertical channel of communication to IT departmental heads, and another horizontal channel of communication to their solution architects' participants. By addressing the departmental heads through dedicated communication, informing them about the survey, the purpose of the study, the expected outcomes, and their entitlement to ask and receive one copy of the research findings that would entice their curiosity and interest to encourage their solution architects to contribute. Moreover, the email invitation to participants of the study explained the analysis relevant to their field of work as IT solution architects. It explained as well their future projects, and the outcomes of the study that would help them to develop their organizational strategic policies, and their entitlement to get access to download one copy of the research findings.

Research Method and Design

The purpose of this scholarly research study was to investigate relationships that may exist between the intention of CCS adoption of the IT solution architects of SMEs in Afghanistan and the independent variables of their perception about the CCS ecosystem PeS, PeP, PeC, and PeN. To achieve this study, I used a correlational quantitative research design. The correlational research has been previously used by researchers in several studies to analyze and conclude relationships among independent, moderate, and dependent variables. This study examined four independent variables to determine their relationships with the intention of adoption of CCS as a dependent variable. The primary purpose of my study was to investigate the relationships between the variables of one single group; I considered the appropriateness to apply a correlational design (Fuzik et al., 2016; Henseler, Ringle, & Sarstedt, 2016; Reio, 2016).

With scholar research, there are three main models a researcher can use, which are qualitative, quantitative, and mixed methods. Usually, the two main methods of research are quantitative or qualitative (Rittichainuwat & Rattanaphinanchai, 2015). In a qualitative method, the main purpose researchers are to answer the how and the why of a phenomenon. Qualitative research is based on developing concepts and theories using either an inductive or a deductive content analysis approach (Gehman et al., 2017; Lewis, 2015; Tarrazo, 2016). In the quantitative methods, researchers are keener investigating the how many, how often, and what relationships are in between the phenomenon variables (Guetterman, Fetters, & Creswell, 2015; Hussein, 2015). Moreover, one more research method not frequently used, which is a mixed method that combines qualitative research followed by quantitative analysis (Guetterman et al., 2015).

Method

Quantitative. The methodology of this study was quantitative for a primary reason in that it allowed me to rely on deductive reasoning. The deductive perceptive, rational analysis has been followed by several previous researchers to investigate about technological problems of IT (Campbell et al., 2017; Moryson & Moeser, 2016; Tarhini, Hone, Liu, & Tarhini, 2017; Xu, Thong, & Tam, 2017). My second reason to choose a quantitative methodology was that it allows me to generalize findings from a specific sample to a broader population. Counsell and Harlow (2017), Onwuegbuzie and Collins (2017), and many others confirmed that the types of quantitative modes of discovery that involve meta-analysis, replication research, and evaluation studies contribute to an empirical generalization of the findings. Montag et al. (2015) said findings could be generalized between similar-cultural countries. I used the quantitative method because I wanted to generalize predictors of my study in Afghanistan to a broader population in similar neighboring countries, such as Tajikistan, Uzbekistan, and Pakistan. My third reason for using a quantitative methodology was that I wanted to know the various causes and what the possible barriers are for IT architects not to adopt CCS as their best technology. However, a quantitative methodology would allow me to attend to a large sample of the population of Afghanistan to understand the relationship between perceptions of understanding of some external operational variables with the intention of adoption of CCS.

Qualitative. Ospina, Esteve, and Lee (2018) said a qualitative study is an interpretive methodology to explain new problems and explore new theories. Lewis (2015) said qualitative methods are used to collect detailed data out of interviews, documents, and other various sources and investigate and analyze contextual information of the study phenomena. Boddy (2016) stated a qualitative methodology requires a researcher to communicate his interviewees' experiences and prospects to probe their perspectives on the topic and phenomenon of study, and through in-depth analysis, uncovers their beliefs, assumptions, and predispositions. Hammarberg, Kirkman, and De Lacey (2016) stated that a qualitative study is viewed with doubt and may be considered trivial as it encompasses small samples for study, which may not be representative of the broader population. Therefore, a qualitative method was not appropriate for my study because; first, the contextual information would be ineffective without having a clear understanding of what key factors affect the intention of IT architects' adoption of CCS in Afghanistan. Second, the purpose of the study was to analyze and understand the relationship between external factors and the testing theory of the study.

In contrast, qualitative research was more concerned with understanding some societal concerns. Saunders et al. (2018) said a qualitative method is a less theory-driven study relying on a narrow analysis to confirm a specific conceptual framework. For this study, a qualitative method was inadequate as it did not meet the purpose of the study that through the proposed ETAM, I needed to test the hypothesis and answer the question of the research.

Mixed-method. A mixed-method qualitative-quantitative design conducts research encompassing the collection of data, dissection, analysis, and integration of first a qualitative design of finding and then quantitative statistical test analysis (Cendán et al., 2017). Because of the inadequacy of the qualitative method of this study, the mixed method was unsuitable.

ETAM framework. The theoretical framework of the study was based on TAM, which was extended to the ETAM of the study by adding PeS, PeP, PeN, and PeC external variables to analyze the behavioral intention of IUoT of the IT solution architects in Afghanistan. Abdullah, Ward, and Ahmed (2016), in their study of TAM investigating the e-portfolios influence on PEoU and PU of students, used a quantitative correlational method to test their proposed model that extended the TAM by adding social, institutional, and individual variables. Abdullah et al. (2016) said the quantitative method of TAM is widely used and that by adding external variables to TAM, researchers, in addition to the large flexibilities to explain technology adoption behavior, can also pinpoint to particular reasons for which the technology may not be adopted. Xu, Thong, and Tam (2017) suggested a strategy to win back technology dis-adopters and proposed a re-adoption model based on TAM. Xu, Thong, and Tam (2017) said quantitative methods of research were used to identify and measure relationships between constructs derived from a theoretical framework such as TAM. Mohammed, Ibrahim, and Ithnin (2016) said TAM was a useful framework to identify the main factors influencing CCS behavioral intention of adoption for e-government implementation using a quantitative method of research.

Conclusion. I selected a quantitative method for this study. I wanted through statistical analysis to analyze the cloud computing adoption phenomenon by (a) identifying the relationships among the variables of interest, (b) through sampling the population of the industry, and (c) by generalizing the findings of the study country-wise as well as region-wise.

Research Design

Campbell and Stanley (2015) stated the availability of the three main research designs used for quantitative methods that would allow the researcher of a study to identify possible relationships between the variables. These three quantitative designs of research are; (a) correlational, (b) quasi-experimental, (c) and experimental.

Curtis et al. (2015) explained that in the experimental design of quantitative research, the researcher modifies deliberately one or more of his independent variables of study to measure the changes' impact that has on the dependent variables. Campbell and Stanley (2015), as well as Ofosu-Boateng (2017), said the design of experiments relies on a statistical design procedure that a researcher would work to make it efficient and reliable for study. Beck (2018) indicated that the experiment should be well planned so that the data obtained can be statistically processed and analyzed to yield valid conclusions. The quantitative cause-effect experimental design was not suitable for my study as I had no human intervention and cause-effect analysis in my design.

Regarding the quantitative quasi-experimental design, Campbell and Stanley (2015) confirmed its usefulness for measuring social variables. Some physical and biological scientists regard quasi-experimental design as being unscientific and unreliable (Antony, Muralidhar, & Kuriyan, 2016; Moylan, Hatfield, & Randall, 2018). Abah (2018) and many others explained the scientific unreliability of a quasi-experimental design associating it to the lack of random allocation of groups and appropriate experimental controls, and therefore obtaining a sound statistical analysis can become very difficult. The quasi-experimental design was not convenient for my study because I was looking for a random sampling of the population and the appropriate reliability and validity of the study. Becker et al. (2017) clarified that the experimental and the quasi-experimental designs require a cause-impact evaluation of a manipulative intervention on the target population without random assignment, and hence are not applicable in this study.

Psychologists use correlational research designs in their research to analyze and understand human behaviors (Isik & Uzbe, 2015; Mulud & McCarthy, 2017). Many other researchers confirmed the efficiency of using correlational designs of research to analyze human behaviors about the diffusion of new technologies and the intentional adoption of users (Boulianne, 2015; Muda et al., 2017; Nieves & Quintana, 2018). The correlational design of research about technology provided an essential paradigm of the scientific and reliable investigation. The correlational design in scientific research is meant to discover relationships among variables that would allow determining predictions of future events from present knowledge.

I have considered for this study to use a correlational design. Bellemare, Masaki, and Pepinsky (2017) used a predictive and correlational analysis for his study. I used a predictive correlational design, without any human intervention manipulating predictors, to assess whether there is a relationship between variables of the study, which are in prediction state and not cause-and-effect.

The purpose of this quantitative correlational study was to examine the relationship between IT solution architects PeS, PeP, PeN, and PeC, PU, and PEoU with the IUoT to analyze CCS adoption. The target population is the technology IT solution architects SMEs in Afghanistan. The independent variables were PeS, PeP, PeN, and PeC, PU, and PEoU, and the dependent variable was IUoT. The study’s findings may promote positive social change by contributing to a reduction in energy consumption and carbon dioxide emission (Kaur & Chana, 2015) once CCS adoption spreads out in developing countries.

In this study, I wanted to increase the predictive power between the variables based on a proposed interrelationship model. Hence, the predictive correlational methodology and design that helped me to predict the variance of my variables based on the deviation of another was the right design of analysis to adopt for this study. Rather the experimental and quasi-experimental designs would not comply with the correlational predictive methodology that I liked to follow.

Population and Sampling

I collected data from IT solution architects of large and medium-sized enterprises in Afghanistan who were the general population of the study. The specific geographic area of the population was the main cities of Afghanistan, such as Kabul, the capital, Mazar-el-Sherif in the Northern region bordering Uzbekistan, Herat in the West bordering Iran, and Kandahar in the South bordering Pakistan. According to the AOE (2010) and MOCI (2016) inputs, there were approximately 10,500 small and medium-sized enterprises running a business in several private sectors such as food manufacturing and distribution, construction, agriculture, furniture manufacturing, healthcare, and ICT. The MOCI confirmed having around 400 SMEs specialized in ICT services, and that at least 3000 IT professionals are employed by the SMEs and were known to the Afghan MOCI at the time of the study (ASMED, 2012).

I collected data from IT solution architects who were the general population of the study. The geographic area of the population was Afghanistan, but the specific areas of the target were the main cities of Afghanistan, such as Kabul, Mazar, Herat, and Kandahar. Since the population I was examining is relatively large, I performed a random sampling where then I distributed the survey to the randomly selected subjects. To accomplish such a plan, I conducted the study in my role as a Walden DIT student. The invitation of participants can be found in Appendix E. The population of the study consisted of IT solution architects working for IT service providers small or medium-sized companies located in Afghanistan. MOCI list of SMEs can be filtered by sectors of industry such as Agriculture, ICT, or Food distribution. MOCI classified the technology sectors under IT, Telecommunication, ISP, ICT, and Electronic supply. Hence, accordingly, the population of the study was obtained by filtering a sub-list of SMEs specialized in technology sectors from the global list of SMEs of the MOCI. The letter of cooperation of the MOCI is in Appendix G.

Moreover, I extracted the sample of study through random auto-extraction from the sub-list using an excel VBAmacro. Buchanan et al. (2018), Onwuegbuzie and Collins

(2017), and Tourangeau, Conrad, and Couper (2014) applied probabilistic sampling to select their participants and ensure reliability. I used a random probabilistic sampling method, which might guarantee an equal probability of selection to the different SMEs solution architects of the various IT industries in the population of the study. Onwuegbuzie and Collins (2017) confirmed that such random of equal probability practice allows calculating a minimum number of respondents to prove the research question. Moreover, and according to Emerson (2015) and Mukerjee, Dasgupta, and Rubin (2018), as a definition, the probability sampling technique is a method of sampling that employs a certain sort of randomized selection. For the random selection, the researcher should set up a procedure ensuring that the population units are all provided an equal probability of being chosen. Tillé and Wilhelm (2017) elucidated that many researchers practiced various ways of random selection by choosing a name out of a hat, or cherry-picking the short straw. However, computers with a simple random generator of numbers program; can provide such a mechanism of picking random numbers and satisfy the need for my probabilistic sampling. de Winter, Gosling, and Potter (2016) confirmed that the purpose of using a random sampling technique is the elimination of sampling bias. However, Tillé and Wilhelm (2017) confirmed that by using a tested computer program for randomized selection will provide a proper probabilistic sampling of study, and hence the sample is, therefore, representative of the entire population.

The sample size required from the targeted population of small to medium-sized organizations was calculated using the software G*Power 3. The G*Power (Erdfelder, Faul, & Buchner, 1996) software is an open-source and was created by the Institute for Experimental Psychology in Dusseldorf, Germany. G*Power was designed as a generic and standalone analysis program for statistical tests that are used mainly in social and behavioral research. G*Power 3 was last current extension of the software with a set of features of improvement over the initial versions (Faul, Erdfelder, Buchner, & Lang, 2009; Walum, Waldman, & Young, 2016). Previous research using the TAM model presented the statistical study based on a multiple regression analysis of the constructs associated with TAM (Abdullah, Ward, & Ahmed, 2016; Gangwar et al., 2015; Mohammadi, 2015; Xu, Thong, & Tam, 2017).

Using the software G*Power version 3.1.9.2, I accomplished an f-test for multiple linear regression to calculate a priori the sample size required for the study. I have used as input parameters to compute the sample size, the effect size, the error probability, the power, and the number of predictors. Hayes and Montoya (2017) and Mortenson and Vidgen (2016) used the TAM theoretical framework, respectively, with a medium effect size (f=0.15), error probability (α =0.5) and power (p = 0.80). I used for my study an f = 0.15, α = 0.05, and p = 0.80 with the four predictors used in ETAM to estimate that I would need a minimum sample size of 85 participants as shown in Figure 13, to accommodate a (p) of 0.8. To increase the (p) to 0.95, I have to increase the sample size to 129. Laconi, Tricard, and Chabrol (2015) in the sampling size of their study applied a balancing average of participants, hence by applying the same logic, I selected a number ranging between 68 and 125 participants for this study.

By reviewing several references, discussing rules of thumbs of sample sizing, such as Wilson VanVoorhis and Morgan (2007), Al-Bayyati (1971), and Jameel (2017) showing several diverse methods of sampling, hence there is not one single rule of thumb for size sampling computation. However, some researchers insist on having at least 10 observations per variable (Aguirre-Urreta & Rönkkö, 2015), as an example, if a researcher has three independent variables of a study, the minimum sample size required is 30 participants. Hanley (2016), demonstrated that sample sizing depends on the type and genre of the research, hence relying on statistical formulas is a better approach, as the outcomes did not support any rule of thumb that specifies a constant (e.g., 30 subjects). Camacho, Boix, Medina, Hibbins, and Sambles (2017) supported the rule-of-thumb based on the formula of $N \geq 50 + 8m$, where N is the number of subjects and m is the number of predictors, to be applied for the statistical regression analysis of multiple correlations. However, O'Sullivan et al. (2016) stated that this formula yields large values of N when $m \geq 7$. Lo, Chair, and Lee (2015) stated that as long as $(m) \leq 6$, the formula $N \geq 50 + 8m$ is most convenient for sample sizing for statistical regression analysis. Since the examined predictors were PeS, PeP, PeN, and PeC; (m) was then equal to 4, and the formula result yielded to $50 + 8 (4) = 82$ subjects that support the G*Power result of 85 participants. Figure 14 is the F-Test graphical representation of the sample size versus power (1- β error prob).

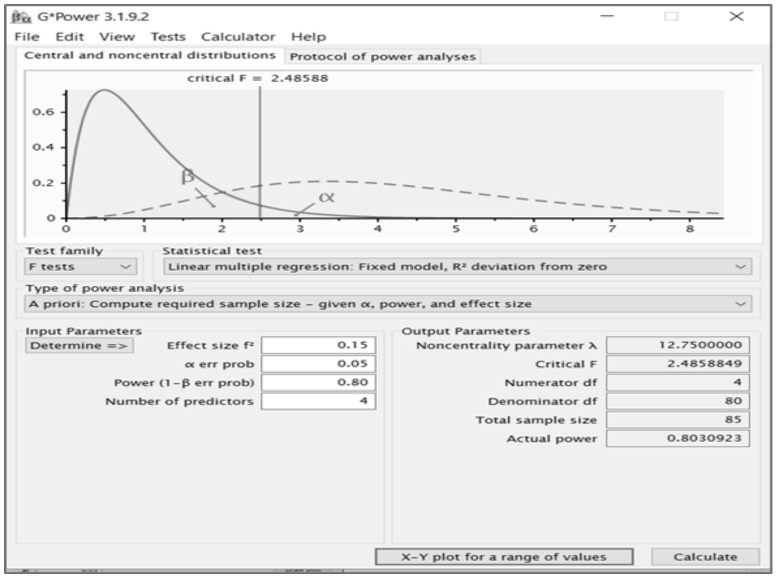


Figure 13. G*Power analysis for sample size computation.

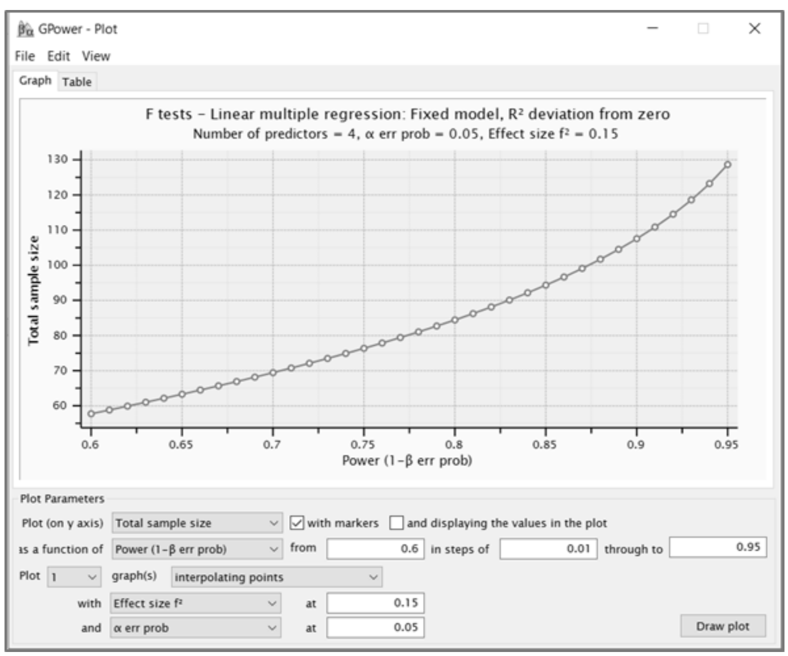


Figure 14. Linear representation of Power versus sample size.

Ethical Research

The Office for Human Research Protections (OHRP) provides the researchers with the rich guidance of leadership to ensure the rights, welfare, and wellbeing of subjects involved in research are protected. OHRP objectives are conducted and supported by the U.S. Department of Health and Human Services. In 1970, The National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research had developed rules and recommendations for human subject protection, including the Belmont Report. In 2000, OHRP had been established in the Office of the Assistant Secretary for Health to lift its position and authority effectiveness. OHRP ensures that its ethical rules are respected and followed by providing the subject experts the needed clarifications and guidance. The role of OHRP is to develop educational programs with related materials, to maintain and ensure awareness of regulatory oversight, and to provide recommendations on ethical and regulatory issues in biomedical and social-behavioral research (OHRP, 1979). However, respecting ethical research behaviors is vital for members of study rights protection. The dogma of ethical research was created when the members of the Nuremberg war crime trials perceived the crucial necessity of a "law of ethics" to protect subjects involved in the research. Hence, the Nuremberg code was issued to arbitrate ethical standards for biomedical investigations and testing. However, the purpose of the code is to educate the researchers to avoid specific identified unethical behaviors that might apply to susceptible individuals participating in biomedical studies (OHRP, 1979). Moreover, data confidentiality of this study was in line with the respect for person principle of the Belmont Report (National Institutes of Health, 1979). As a pre-qualification of research ethics, I also completed the prerequisite certification by the National Institutes of Health (NIH) Office of Extramural Research, No. 2394255, with the training designation of Protecting Human Research Participants (see Appendix B).

I collected data for the study from an online survey that was distributed to all participants in the study through an email of invitation (see Appendix E). The data collected were treated as confidential data and needed to be safeguarded from known vulnerabilities, unauthorized access, and disclosure. To ensure the right ethical collection of data was applied in my survey, I designed the instrument of study to show an informed consent on the first page of the survey. The participants were invited to read the informed consent very carefully and confirm the context understanding and acceptance by, after reading, clicking a checkbox at the bottom of the page.

Roberts and Allen (2015), stated that online surveys were ever more used in academic research postulated an easy and efficient method to collect data and to apply the required norms of ethics of conducting research resourcefully. Having the informed consent at the first page of the survey ensured appropriate reading and understanding before the start of the survey, and having the participant to click on the checkbox indicated his/her signature that he/she had understood and agreed to participate in this research. The consent form was well structured and easy to understand. Hence the participants can make an informed decision to participate in the study.

Clarke et al. (2018) emphasized the ethical need for an informed, voluntary consent objective in the research, and that applies when the researcher provides sufficient information to his participants much before the beginning of the survey. In the informed consent, the participants learned that they could leave the survey and discontinue the work at any time, as well they could skip any of the questions if they felt uncomforted and none of the data would be stored at that time. The participants were informed that after submitting the survey, the data could not be withdrawn because the survey was anonymous, and there was no way to identify which data belonged to a specific participant. The consent form clarified the data confidentiality measures, and that information will be stored in electronic files on a USB flash drive and kept in a safe-box for a minimum of 5 years. The informed consent clarified as well the type of incentives by instructing that the participation in the survey of the study was voluntary, unpaid contribution, and valuable for the professional communities. The professional communities may have learned, from the study findings, about the reason why an IT solution architect will or will not decide to adopt cloud computing technology in Afghanistan.

Moreover, the study findings may, as well, help the IT solution architect to know more about the pros and cons of cloud computing services and to build a clear strategy of adoption. The consent identified the criteria of eligibility to participate in the survey if the participant did possess fluency in English, he/she was a member of the Information Technology professionals, he/she had at least two years of experience in IT solution architect, and he/she was familiar with cloud computing technology. Roberts and Allen (2015) listed important tasks of ethics that a researcher has to address in the informed consent when using an online survey. Roberts and Allen (2015) explained that the consent form should outline the purpose of the study, the criteria required for participating in the study, the right of the participant to engage in a process for withdrawing from the study, data privacy and safeguard, representation of benefits and incentives, and the publication intent of findings. Nijhawan et al. (2013) stated that informed consent is achieved by communicating a consent form asking the participants to carefully read and acknowledge back before they start partaking the survey. Mumford (2018), in his Psychological analysis of the informed consent process, concluded that the participant should be aware of and understand all aspects of the trial and their consequences. Grady (2015) stressed that the participant should understand his voluntary participation and that he can withdraw from the survey at any time. Therefore, the informed consent of this study revealed to participants the purpose of the study, the anonymity of their answers, the security of the data collected, the voluntary participation with description of the incentives and benefits, the right to skip any of the questions or to discontinue the work at any time, and explained that after submission work withdrawal was not possible due to the anonymity nature of the information.

In addition to the measures of ethics addressed in the informed consent of the study, I was involved in leading technology departments for telco businesses in the Middle East as well as the East-South of Africa since 2004, where I have been as an IT leader connected with most IT suppliers and IT professionals of the region. I avoided any coercion by eluding to select participants with whom I ever had dealt on a professional basis. Miracle (2016) of the Belmont Report dictates that by preventing coercion techniques, researchers do obey rules of ethics to evade any ethical violation, and hence ensure their study of ethics validity. Mahon (2014), about force choice and coercion explained in his analysis of internet research and ethics that participants should not be forced or manipulated by any mean.

Data Collection

Instruments

This study was a correlational nonexperimental that employed a VSI for data collection. I eliminated the need for a pilot to test the reliability and validity of the instrument by using a pre-existing survey of a credible previous study that met the scholar criteria of reliability and validity. The data collection method relied on an online survey web tool. For the statistical analysis of the collected data, I used the Statistical Package for the Social Sciences (SPSS) of IBM version 25.

I collected data using a survey with closed-ended questions based on an existing study of IT using the TAM model. The VSI was adapted from the equivalent measures in the original instrument consisted of items from TAM and TAM2 and developed by Davis, Bagozzi, and Warshaw (1989). Venkatesh and Davis (2000, p. 194) tested the instrument in several studies and confirmed that all measurement scales performed high reliability, with a Cronbach’s alpha coefficients exceeding 0.8, and that the principal components analysis of the construct validity was proven strongly supported. Ross (2010) testified a 0.94 Cronbach alpha coefficient for adding external variables to TAM. Lease (2005) stated in his study that the questions relating to the test by adding external variables to TAM of perceived benefits, perceived security, and perceived reliability demonstrated a 0.94 Cronbach alpha coefficient. Obinkyereh (2017) used the TAM instrument to perform the test by adding external variables of perceived security, perceived benefits, and perceived accessibility and demonstrated a 0.83 Cronbach alpha coefficient of reliability. I picked Obinkyereh's (2017) instrument survey questions because the similarity of the TAM framework is close to mine by adding perceived security, perceived benefits, perceived accessibility to TAM to predict the influence on the intentional adoption of CCS in a developing country like Ghana in Africa. I slightly modified the instrument survey of Obinkyereh (2017) to adapt it to the ETAM framework of this study to investigate the external predictors PeS, PeP, PeN, PeC, PU, PEoU. I manipulated a few questions by a slight rewording to reflect the specific predictors of the ETAM of the study. Ibrahim (2014) modified the TAM instrument, added specific external factors of security, performance, compatibility, and adaptability. Ibrahim (2014) used TAM in a predictive study to investigate CCS adoption in the USA. Ishola (2017) used the TAM instrument, added external factors of security, privacy, accessibility, and awareness, to complete his study of TAM to analyze CCS adoption in Nigeria. However, the minor adaptation of the instruments to fit my study did not affect its validity. The Tables of Appendix-A present the survey questionnaire of the study, which is designed to measure IT solution architects' intentions of adoption of CCS based on their perceptions of security, privacy, complexity, and connectedness (see appendix A).

The reliability of an instrument is the degree to which the measures are error-free and can produce consistent results (Lease, 2005). Flower, McKenna, and Upreti (2016) defined reliability as being the degree of consistency between two ratings of the same measurement. Cook, Zendejas, Hamstra, Hatala, and Brydges (2014) confirmed that instruments of research are considered reliable when are used previously by other researchers to obtain similar results. Therefore, the reliability and validity of this instrument are demonstrated through its subsequent use by other researchers thoroughly proving its consistency and trustworthiness (Davis, 1989; Dawson, 2015; Hovav & Putri, 2016; Lease, 2005; Ross, 2010; Stavinoha, 2012; Yoon, 2009). However, Obinkyereh (2017) test consisted of 150 participants that 135 of them responded appropriately with a response rate of 90%. Nevertheless, 67% of the respondents worked in the IT industry for more than a year, and 35% scored high awareness of cloud computing technology against only 3% with low awareness, in addition to a 0.83 Cronbach's alpha for the five points Likert scale survey items.

The instrument of this study was a Likert-type scale that each of the questions is a probing inquiry tailed by a 5 points scale of measurement from lowest to highest: strongly disagree, disagree, neutral, agree, and strongly agree, that which is ranked respectively as 1, 2, 3, 4, 5. As per the study's hypothesis and question, the original VSI was amended to match the need for measuring the perceptions of the participants about cloud computing security, privacy, complexity, and connectedness to conclude their decisive intention to adopt CCS in Afghanistan. The collected instrument's data would allow analyzing and measure, through the series of questions of 5 points Likert Scale, the five predictors of study: PeS, PeP, PeC, PeN, PUse, and PEoU. However, the design, layout, and structure of the instrument questionnaire left intact to ensure its validity and reliability.

From a validity perspective, the study ensured to achieve internal and external validity, as both validities were vital in quantitative research. Venkatesh, Brown, and Bala (2013) confirmed that validity solidifies the legitimacy level of the study. Bell, Bryman, and Harley (2018) stated that research validity ensures the used instrument can achieve the right measurements it was made for and to provide the required results. Bell et al. (2018) subjected that the internal validity verifies a good match between the study observations and the theoretical ideas and ensures the data collected supports the theory. However, the external validity refers to the degree to which the research finding is used for generalization. Field (2017) stated that for a survey instrument to be valid, first, it must be reliable, and therefore, the reliability can be assessed by testing and re-testing to produce a similar score. However, and as mentioned above, the VSI of this study was tested and re-tested in previous studies. Dawson (2015) and Field (2017) suggested conducting reliability testing every time the data and sample change because the population of a specific study is different from the other population studied. Lease (2005), for the survey instrument pre-test, suggested a sample size between 15 to 30 participants as being ideal. I used a sample of 10 participants in the pilot survey to pre-test the survey instrument. The purpose of the survey instrument pre-test was to check whether respondents will have any difficulty to understand the questions, or there is an ambiguous or biased question in the survey instrument (Field, 2017). The SPSS scale test of Cronbach alpha was used to check, using the data collected from the pilot; to demonstrate the consistency and reliability of the survey instrument. Field (2017) and Lease (2005) confirmed that the reliability score of 0.7 Cronbach alpha is an acceptable consistency measure.

The permission for using the survey instrument for my study was requested through email communication, and the approval of Dr. Williams Obinkyereh was granted (see appendix C). From a linguistic issue perspective, English was a second language in Afghanistan. However, all participants could answer the survey in English.

In the instrumentation of this study, I have adopted a self-completion survey administration procedure to manage and collect data. Gnambs and Kaspar (2015) said the self-completion administration procedure of a research instrument is a survey questionnaire that is entirely managed and completed by respondents for the data gathering. Gnambs and Kaspar (2015) said the self-completion administration surveys could be used interchangeably for research because both types of self-completion and assisted-completion produce equivalent scores overall. Chatterji et al. (2017) stated that some of the main advantages of the self-completion administration survey are tools for quick data collection that provide direct and easy access to respondents, and cheaper to administer.

Data Collection Technique

I administered, for this study, a web-online survey questionnaire using Survey Monkey. Roberts and Allen (2015), Chatterji et al. (2017), and Kyte, Ives, Draper, and Calvert (2016) said the reliance on online surveys in research increased because of several benefits of return to the researcher, such as being a cheap method, flexible, easy to administer, and provides a quick access to many types of participants. I addressed the survey participants who are the IT solution architects. The survey participants received an invitation to participate in the survey through their personal or business inbox email. I collected the population list, who are the IT solution architects of SMEs were running a business of technology services in Afghanistan at the time of the study, from MOCI (see appendix G). I randomly selected the potential participants of the study from the MOCI list. I conducted the study in my role as a Walden DIT student. I invited the participants of the study to participate in the survey through an email of invitation (see Appendix E) using my Walden academic exchange account. Howe, Chen, Heitner, and Morgan (2018) said the email of invitation to participants is efficient if linguistically is well crafted. Kratzke and Quint (2017) said the email communication is not just convenient for the researcher to encourage participants to join the survey, rather also to recipients who would feel concerned to contribute if the email is well crafted. Roberts and Allen (2015) in their recommendations about research ethics, upraised online surveys in the research industry, and confirmed its upsurge as being the preferred model for data collection among contemporary researchers.

The online data collection process was monitored daily for responses. I was sending reminders to participants to increase the respondents' ratio and speed up the process. After the data collection period ended, I downloaded the data from Survey Monkey and stored it on a flash drive for further analysis. The survey's downloaded data was uploaded into SPSS version 25. On the SPSS, the files produced from the analysis were historically maintained and backed up to protect the research integrity.

Data Organization Techniques

The survey's statistics of contribution progress was reviewed every day. Emails reminder to participants was being sent every 4 to 5 days to encourage them to respond to the invitation to participate in the survey. After 16 days from the date of sending out the email invitation, I blocked the access to the survey and proceeded with the collection of the data. I downloaded the collected data from Survey Monkey, and I deleted it from the SurveyMonkey platform to avoid any risk of any external or accidental internal unauthorized access to data. I stored the raw data on a flash USB disk, and locked it in a safe box and will be kept for five years. After completion of 5 years period, The USB drive will then be destroyed to prevent any restoration of the deleted data from the flash drive in case it is reused. The raw data will be available upon request, from the researcher, within the five years of data being stored.

Data Analysis Technique

This research study, data collection, and analysis procedures and techniques tried to answer the research question through hypothesis testing. The goal was to analyze any existence of a relationship between the identified variables of this study; PeS, PeP, PeN, PeC, PU, PEoU, and IUoT by the IT solution architects in Afghanistan. The independent variables were PeS, PeP, PeN, and PeC, the variables moderators were the PU and PEoU of the TAM, and the dependent variable was the IUoT by the IT solution architects of the SMEs in Afghanistan.

Research Question

The research question (R_Q) that this study was supposed to answer was: What is the relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with IUoT of the IT solution architects of SMEs in Afghanistan? And accordingly, the research null hypothesis (H_0) this study will try to test was: There is no relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, PEoU with IUoT of the IT solution architects of SMEs in Afghanistan.

Analysis Method

I collected the data of the study for analysis via SurveyMonkey, which is an online web-based survey tool, to respond to the research question and to test the related hypotheses. The purpose of this correlational research was to describe the relationship between the ETAM predictors and the dependent variable. My preference analysis technique for this study was inferential statistics. Gibbs, Shafer, and Miles (2017) said the inferential statistics of parametric procedures such as t-test, ANOVA, and linear regression used for predictive purposes. There are other inferential statistics of nonparametric procedures such as the Chi-square test and Spearman's rank correlation coefficient used for predictive analysis as well. Unlike inferential statistics, the descriptive statistics are used to label and define data that allows an examination of the central tendency between the variables (Jankowski & Flannelly, 2015). The descriptive statistics do not allow inferences analysis among the variables. This study analysis relied on an inference methodology of multiple regression analysis because I needed to find a relationship between the sample and the population. I used the descriptive statistics for this study to present a graphical summary of the data, such as bar charts, histograms, and scatter diagrams.

With the multiple regression analysis of this study, I identified whether the independent variables PeS, PeP, PeC, and PeN and their moderators PU and PEoU might have any substantial relationship with the dependent variable IUoT of CCS by the IT solution architects in Afghanistan. The multiple linear regression was defined as being the most common form of single linear regression analysis (Adebayo & Suleman, 2017). For the predictive analysis, I used the multiple linear regression to demonstrate the relationship between the dependent variable IUoT, and the four independent variables PeS, PeP, PeC, and PeN.

I analyzed the collected data using the SPSS release 25, which is an IBM software tool for statistical analysis. The data collected was born of the answers to the online SurveyMonkey survey's questions, with a five-point Likert-Scale. The survey questions were ranging from strongly disagree to strongly agree, respectively, from 1 that is representing strongly disagree to 5 which is representing strongly agree (see appendix A). The survey questions were grouped into six main groups representing the four predictors' constructs and the two moderators relating to the ETAM framework of this study. In the Survey, we had two types of questions: (a) standalone and (b) serialized. Subedi (2016) said the standalone questions should submit a Likert-type examination using modes, medians, and frequencies. The group serialized questions in surveys meant those combined to measure one particular trait; for example, the group of four questions used in appendix A to measure PEoU. Liddell and Kruschke (2018) said the serialized type of questions might be treated using Likert-types to examine means and standard deviations.

Among the inferential statistics methods, t-Test, ANOVA, and factorial ANOVA were not suitable for this study. T_Test and ANOVA are used to test multiple groups and check for the variances between them (Jankowski & Flannelly, 2015). This study evaluated the behavioral intention of one group, which was IT solution architects in Afghanistan. Gravetter and Wallnau (2016) and Lin, Featherman, and Sarker (2017) said the correlation analysis used to demonstrate how two variables correlate of changing together; hence, the correlation analysis was not suitable for this study either. However, the multiple regression analysis was ideal for my study because the purpose was to investigate a significant relationship of prediction among the independent variables (X) with the dependent variable (Y).

Descriptive Statistics

Grant, Ries, and Thompson (2016) believed that the use of descriptive statistics is essential for any research. The factors descriptive analysis provides a comprehensive compendium, and abridgment to the data homogeneity, as well as an insight into the internal data validity. Johnson, Lewis, and Reiley (2016) supported such a methodology of using a statistical description of the data as a sort of validation to succumb trustworthiness in the study. I performed a univariate analysis of data normality, which included; (a) the distribution, (b) the central tendency, and (c) the dispersion descriptive analysis presentation of the variables.

Distribution analysis. The distribution analysis was examined through a descriptive frequency distribution analysis. According to Di et al. (2016), once a frequency distribution is well constructed, it can allow making a detailed analysis of the population structure concerning a single quantitative characteristic. If the values of frequency distribution analysis outcome are ordered and arranged based on balanced increasing or decreasing magnitude, then the frequency distribution is said to be ranked.

Central tendency analysis. The central tendency analysis is a single value that attempts to describe a set of data by identifying the central position within sets of data. According to Burke, Cohen, Doveh, and Smith-Crowe (2018), the mean, median, and mode are used to measure the set of data curve center, that which it allows the researcher to; (a) identify the central location of data sets, (b) identify the area where most of the data lines, (c) identify positive and/or negative skewness, and (d) can detect outliers based on plot graphs of distribution. The central tendency helps to insight the behavior of data.

Dispersion analysis. The dispersion analysis indicates the lack of uniformity in the size of items of a series. Weir et al. (2018) confirmed that the Standard Deviation is an accurate evaluation of dispersion in a data set because any of the outliers if exist, can seriously overstate the range. I used descriptive statistics of data normality such as bar charts, histograms, and scatter diagrams to summarize a statistical representation of the data.

Missing Data Verification

Koszalinski, Tansakul, Khojandi, and Li (2018) recommended that before every statistical analysis, raw data must be screened and validated for both cases of adjusting the missing data, as well as outliers, check. Hence, best practices in data analysis dictate to treat missing data for cleanup and the outliers for careful imputation of values, which is an essential pre-requisite before proceeding with the analysis. Kumari and Kennedy (2017) stated that data cleaning task requires careful considerations because it affects the final results of the statistical analysis. Koszalinski et al. (2018) confirmed that cleaning the data demands permanent consistency in checks and accurate treatment of missing responses, which generally is done through professional tools such as SPSS. The consistency checks of missing data cleanup serve to identify data which are out of range, inconsistent, or data that have illogical extreme values such as outliers (Koszalinski et al., 2018; Baur et al., 2015). Hence, through SPSS, I carefully treated the missing responses to minimize their counter effects by assigning a neutral or imputed value or by discarding them methodically. There are several cases to treat an appropriate and careful cleanup of the missing data. However, I mainly followed to apply two methods: (a) Deletion of cases, which is the fact of deleting from the raw data collected the cases that represent missing data on any of the variables. (b) Mean substitution, which is for each missing data value; we impute the mean; imputation is the replacement with an estimated value, which is, in this case, the Mean value of the variable. According to Baur et al. (2015), missing responses may cause significant problems if their proportion to the total volume of responses is greater than 10%.

Assumptions Analysis

Linearity assumption. The linear regression analysis seeks to prove a linear relationship between the independent and dependent variables. Hence, the linearity assumption can best be tested with scatter plots, and also it is important to check any outlier because the linear regression is susceptible to outliers' effects.

Deal with outliers. There are three different statistical methods to deal with outliers' impact mitigation: (a) Univariate technique - it looks for extreme values on one independent variable, (b) Multivariate technique - it looks for strange combinations on all the variables and usually is used to mitigate Type I errors. (c) Minkowski error – is the best method as it reduces the contribution of the looming outliers in the process.

Normality assumption. The linear regression needs all variables to be multivariate normal. Therefore, a normality or a multivariate normal needs a stable distribution of the variables bunching around the mean value. The normality assumption is checked through a fit-test. The most familiar fit-test is the Kolmogorov-Smirnov test, and as well it is best observed through Q-Q-Plots and histograms (Hu, Yu, & Wang, 2016). There are too many reasons that may cause normality assumption to fail some of them are: (a) outliers that can cause data to be skewed as the mean is very sensitive to them, (b) a multiple distribution maybe is combined in the data that would cause the presence of a multimodal distribution, (c) insufficient data could be behind the reason of a normal distribution to look completely scattered.

Deal with normality violations. When data fails to fulfill the normality assumption, a non-linear transformation such as a log-transformation may help to fix this issue; that means to perform regression using the logarithm of the variables $log\ x$ and $log\ y$ instead of the original ones x, y. Hu, Yu, and Wang (2016) suggested other alternatives of statistical tests to deal with the lack of normality, including the one-sample Z test, T-test, and ANOVA test.

Multicollinearity assumption. The third statistical assumption is that linear regression assumes there is no multicollinearity in the data. The multicollinearity occurs as a problem if the independent variables are significantly interrelated with each other. According to Winship and Western (2016), the multicollinearity analysis is a detected effect when predictors, as well as the dependent variable in the linear regression, present a problem of large standard errors due to near-linear dependencies among them. Multicollinearity can be tested with several criteria for assessment by using the correlation matrix (CM) or the variance inflation factor (VIF) technique. The CM test assumes to find in the matrix of Pearson's Bivariate Correlation a correlation coefficient

< 1 among all variables. In the VIF test, a value of VIF > 10 assumes there is an indication of insignificant multicollinearity, while with VIF > 100 the multicollinearity among the variables is certain (Goodhue, Lewis, & Thompson, 2017). Winship and Western (2016) stated that the CM allows the researcher to compute the coefficients of determination regressed on the remaining predictor variables and to measure the condition index. I examined the bivariate correlations of a high coefficient of correlation among the variables to ensure they are less than 0.8. As such, this indicated that there is no influence on the correlation among the predictors as well as between any of the predictors and the dependent variable (Lin et al., 2017).

Deal with multicollinearity violations. When data fails to fulfill the multicollinearity assumption, centering the data - which means deducting the mean of the variable from each score - can help to reduce the multicollinearity effect. There is a simpler way to address the multicollinearity problem, which is to remove the independent variable that is found with high VIF value. Another alternative to tackle the multicollinearity problem is to conduct a factor analysis by rotating the factors and ensure the independence of the factors (Disatnik & Sivan, 2016; Goodhue et al., 2017), as well as Ridge Regression and Principal Component Regression tests, are good methods to fix multicollinearity problems (Dorugade & Kashid, 2010; Salmerón, García, García, & del Mar López, 2018;).

Autocorrelation assumption. The fourth statistical assumption of linear regression to consider is autocorrelation. There should be no autocorrelation or significantly little of it in the data. The autocorrelation problem may occur when the residuals are significantly dependent on each other (King, 2018). In regression analysis, the distance between the observed value of the DV (y) and the predicted value ($\hat{y}$) is called the residual. So, the residual value can be obtained by applying the formula *residual = observed value - predicted value*. In other statistical words, autocorrelation occurs when the value of $y(x+1)$ is not independent of the value of $y(x)$. King (2018), as well as, Alao, Mati, and Jacob (2016) stated that in the linear regression model, the autocorrelation could be checked by Durbin-Watson's test. Durbin-Watson's test checks the normality of the residuals that are not linearly autocorrelated. The test outcome assumes the value (d) of Durbin-Watson's test should be falling between 0 and 4 ($0 \leq d \leq 4$), and hence, values around 2 ($d \approx 2$) indicate no autocorrelation. King (2018) determined a rule of thumb that the values of $1.5 \leq d \leq 2.5$ would show that there is no autocorrelation in the data.

***Deal with autocorrelation violations*.** When data fails to fulfill the autocorrelation assumption, as per Anderson (2012), correction is possible by applying the generalized least squares (GLS), which is a statistical technique to estimate the unknown parameters when a significant degree of correlation is found between the residuals in a regression model. Another alternative is suggested by Anderson (2012) as well, which is to include a linear term or trend if the residuals distribution pattern demonstrates a steady increase or decrease.

Homoscedasticity assumption. The fifth and the last assumption of the linear regression analysis is the homoscedasticity, which means the residuals are equal across the regression line. Homoscedasticity is also understood as the homogeneousness of variances. The violation of homoscedasticity is called heteroscedasticity. Homoscedasticity assessment could be checked based on scatter plot analysis between residuals and independent variables, as it undertakes that the error variance is constant across all observations in the data set (Alao et al., 2016). Durbin Watson test is one of the statistical techniques to test homoscedasticity, which is an accepted method of testing whether IVs' correlations do not affect the predictability of the DV (Jacob et al., 2014). A Durbin Watson value ranges from 0 to 4, where the number 2 means that there is no correlation between the independent variables (Alao et al., 2016; King, 2018).

Deal with homoscedasticity violations. When data fails to fulfill the homoscedasticity assumption, it means that data is heteroscedastic (homoscedasticity is present). Thus, a nonlinear transformation may correct and fix the homoscedasticity problem. A nonlinear transformation helps to increase or decrease the linear relationships between the variables and accordingly amend the correlation among the residuals. For example, in such a transformation, we take ($\sqrt{x}$) instead of the variable (x). Practically, statisticians rely on an alternative solution, which is the ordinary least-squares (OLS) regression that helps to minimize residuals and to produce smaller standard errors. Rahman et al. (2018) stated that OLS regression provides equal weights to all observations. Lee, Huang, Liu, and Lan (2019) suggested that in most cases of heteroscedasticity's problem mitigation, the weighted least squares (WLS) regression is more appropriate as it further down-weights observations with higher disturbances.

Sample Size

For the inferential results' interpretation of the multiple linear regression of this study, I conducted an F-test to calculate *a priori* the needed sample size. I considered as a given, the effect size ($f = 0.15$), the error probability ($\alpha = 0.05$), the power ($p = 0.8$), and the number of predictors ($IV = 4$) used in the TAM to estimate, what has been demonstrated in a previous section, that I would use a sample size of $85 \cong 115$ participants. With a $\alpha = 0.05$ helps to range an acceptable probability of the type I error, and $\beta = 0.2$ is the acceptable probability of type II errors, and $1 - \beta = p = 0.8$ is equal to the power. If the power *p-value* increases with different levels of α, the sample size will also increase. In a correlational analysis, Cohen's (1988) conventions are used to interpret the effect size. Gignac and Szodorai (2016) stated that for multiple regression analysis, the effect size is based on Cohen's $f2$ interpretation. Cohen's interpretation makes use of equivalence between the standardized mean difference (d) and the correlation coefficient (r), using the formula $f^2 = R^2/(1 - R^2)$ where R^2 is the squared multiple correlations (Cohen, 2013; Gignac & Szodorai, 2016). Cohen (1988, 2013) provided guidelines for the interpretation of the magnitude of a correlation while considering the power estimation. The values of $r = 0.1, r = 0.3, and\ r = 0.5$ were suggested for consideration respectively as small, medium, and large in magnitude. A correlation coefficient of $r = f = 0.15$ is assumed to represent a weak or small association between variables.

Study Validity

This research was a quantitative correlational study focusing on SMEs' adoption of CCS in Afghanistan. To ensure the collected data reliability, I distributed the survey to the IT solution architects of SMEs registered at Afghan MOCI specialized in information and telecommunication technology sectors. There were approximately 4500 registered SMEs in Afghanistan, among which around 400 of them specialized in ICT services. These SMEs were mainly distributed in the main cities of the capital Kabul, Mazar, and Herat at the time of the study.

Possible Types of Errors

In scholar studies, the purpose of a researcher is to demonstrate or invalidate the null hypothesis of the study and support the observations through evidence obtained during the research study (Curran, 2016; Hales, 2016). Type I error, known as the alpha error, is the incorrect or false conclusion that a difference exists, which means is the rejection of the null hypothesis while it is true. The likelihood to commit type I errors abbreviated as (α) is by convention equal to 0.05. Type II error, known as the beta (β) error, is the incorrect or false conclusion that a no difference exists while there is, which means the researcher fails to reject the null hypothesis while it is false (Akobeng, 2016; Hales, 2016; Sainani, 2018). Hales (2016) said the possibility to commit type II errors abbreviated as (β) is by convention equal to 0.2. Therefore, Type I and II errors are mutually exclusive; the more the decreasing of the risk of a Type I error, the more increasing the chances of a Type II error. The scenario is explained in Table 1 below;

Beukelman and Brunner (2016), who stated that the experimenter is more willing to make a type II error than a type I error.

Table 1

Summary of Types of Decision Errors

True Situation	**Accept H0**	**Reject H0**
H0	Correct	α error
Ha	β error	Correct

From Beukelman and Brunner (2016); illustrating the concepts of the null hypothesis and α and β errors.

Moreover, Type III error, known as 0 errors, occurs when a researcher gets the right answer to the wrong question. Hales (2016) explained that Type III errors are rare, as they only happen when random chance leads to collect from the group low values that are in reality, higher or higher values than what are. The Type IV error is a specific type of Type III error. Type IV error happens when the null hypothesis is correctly rejected, but results are interpreted with mistakes. Some common reasons for Type IV errors are (a) Aggregation bias, (b) Running the wrong test, or (c) Collinearity among predictors.

Null Hypothesis versus Errors Type

In this statistical decision model, the deny of the null hypothesis as a requirement of analysis will be based on three possible outcomes. Hales (2016) said first if the null hypothesis is true with good evidence, then it is verified, and I have no errors. Second, if the null hypothesis is false, then I may have a Type I error, and third, if the null hypothesis is true with bad evidence, then I may have Type III error. In this study, my null hypothesis stated that PeS, PeP, PeC, and PeN do not directly influence PU and PEoU, which in turn do not influence the dependent variable IUoT.

Dealing with Type I and II Errors

In this study, I aimed to disprove my null hypothesis based on good evidence to support my decision and mitigate Type I and II errors. Hence, to ensure statistical conclusion validity, I used VSI that has been used in previous research studies. Moreover, I have considered the factor validation Power, which is the ability of a statistical test to identify a true difference if one exists expressed mathematically by $(1 - \beta)$. The Power is a consideration in the design of an experiment as the Power of the test is affected by the sample size (Beukelman & Brunner, 2016). I aimed in this study for a sample size of a medium to high Power. Statistically, the probability of a type I error (rejecting a true null hypothesis) was mitigated by selecting a reduced value of significance $\alpha < 0.05$ (necessitating a smaller *p-value* for rejecting H_0). Therefore, with a smaller α value, the probability of a type II error (failing to reject a false null hypothesis) was mitigated by selecting a bigger sample size.

External Validity

Another characteristic of validity is needed to be examined to validate this study was external validity. External validity refers to the ability of the researcher to extend his research findings based on the sample of individuals he selected, to be generalized to the same population the sample is taken from or to other similar populations in terms of contexts, individuals, times, and settings (Bell, Olsen, Orr, & Stuart, 2016; Hales, 2016). This study dealt with IT solution architects of the SMEs in Afghanistan. However, other researchers can apply the same research design to other industries within Afghanistan, such as medium-sized firms of mobile operators, Internet service providers, healthcare, and education institutes. This study outcome can be extended to other industries ' populations because I relied on the sampling performance to reduce the external validity risk as Hales (2016) and Bell et al. (2016) confirmed that a good sampling method could lower external validity threats. Threats to external validity can be any of the factors that might affect the study generalizability of the findings. These factors include: (a) selection biases – happens when the sample of the study does not represent the population which can be avoided by random sampling and appropriate sizing; (b) the real world versus the experimental world – happens when either participants' effects, instrumental effects, or experimenter effects influence the outcome of the experiment which can be avoided by appropriate validity of the instrument by providing a structured informed consent as per NIH recommendations; and (c) history effects and maturation – happens when any social, political, or economic event impacts the environment that changes the study's conditions or setup and hence affects the outcome (Pearl & Bareinboim, 2014; Petursdottir & Carr, 2018). In the event that a future researcher wants to examine a different developing country of similar populations in terms of contexts, individuals, times, and settings, it is verified that there is a possibility that the groups SMEs do have common business requirements with IT systems for their daily operation (Brunswicker & Vanhaverbeke, 2015; Ghobakhloo, Hong, Sabouri, & Zulkifli, 2012; Taylor, 2015;). Then the findings of this study can be generalized, and future researchers can extend the same research to other similar developing countries.

Internal Validity

One more important aspect of validity to consider is internal validity. The internal validity is a phenomenon of control referring to the wellbeing research is executed. Internal validity would allow the researcher to analytically choose among alternative explanations of findings (Halperin, Pyne, & Martin, 2015). Petursdottir and Carr (2018) stated that studies of high internal validity allow researchers to choose one explanation over another with high confidence without tolerance to confusion. There are several different factors that affect the internal validity of a study that can be threatened or jeopardized: (a) history – these are events happening to participants during the research and that affect results without being linked to the independent variable, (b) reliability of measures and procedures – due to an unreliable or inconsistency in the ways instructions are given to participants, which can be avoided through unified communication and instrumentation; (c) using design of low power – due to small sample sizing that may have low power of detecting a real effect, which can be avoided by sizing appropriately the sample; (d) order effects - due to participants who are becoming bored, disinterested, fatigued, tired, or less motivated, which can be avoided by limiting the survey size and easy to understand its questions. However, as significant controls were added to the instrumentation and data collection technique of this study, the internal validity is increased.

For this research, I used an online survey instrument of TAM consisted of a grouped set of questionnaires (see appendix A) that was successfully used in previous studies involving IT in both developed and developing countries. Future researchers can replicate the study by using the same survey instrument and the methodology of data analysis. Due to the rapid progress and developments of technology, especially in cloud computing infrastructure as well as in Internet services, the adoption of solution architects of CCS in developing countries might present different results after a few years from now. However, the research design, data collection, and methodology of analysis would remain the same, but the outcomes and findings might be different as the years go by.

Transition and Summary

Section 2 reiterated the purpose statement. This provided in-depth information regarding goals set for this research study, participants, population and sampling, and research methodology and design. Additionally, the section involved detailed ethical discussions, which were critical for the researcher of this study to abide by the Walden's IRB and Belmont report ethical requirements, practices, and obligations. Section 2 contained information about the population and related sample selection with descriptive information regarding how the study protected participants. Section 2 also included data collection and data analysis, as well as the choice of instrument, data collection, data analysis techniques, and how the study ensured study validity.

Section 3 presents a statistical analysis of the collected raw data and an overview of the whole study as well as findings from collected data analysis. Additionally, Section 3 includes multiple regression models and frequency tables to back the inferential analysis. Finally, Section 3 extends the application of the findings into professional practices, implications for social change, and recommendations for actions and further studies.

Section 3: Application to Professional Practice and Implications for Change

In the previous sections, I presented the background of the study, elaborated on the problem and purpose statements, explained the research question and hypotheses, described the nature of the study, discussed the theoretical framework I used, and reviewed relevant academic literature. I used a quantitative correlational method to identify the relationship between the four external independent variables and the dependent variable. The external variables were PeS, PeP, PeN, and PeC, as well as the two core mediators of the TAM, namely PU and PEoU, and hence, the dependent variable was IT architects' behavior IoUT.

In Section 3, I present an overview of the study, presentation of the findings, characteristics analysis about the instrument, characteristics of respondents, and data collected where data collection characteristics analysis encompassed an in-depth representation of data reliability and validity. I present a multiple linear regression analysis and restate a summary of study findings and discuss how they would improve IT practice. I also discuss the implications of the research in terms of social change and offered recommendations for further studies.

Overview of Study

I used Pearson's coefficient and multiple linear regression to test for any existing relationships between the independent variables PeS, PeP, PeN, PeC, and the moderators PeU and PEoU with the dependent variable IoUT. To ensure that outcomes were statistically valid, I indicated the level of marginal significance 0.05 as the p-value for the statistical hypothesis test. The Pearson's coefficient (*r*) analysis showed a significant correlation between IoUT and the independent variables PU, PEoU, PeS, PeP, and PeN, but not PeC. Results of the tests exposed substantial correlations between IoUT and PeS where $r(121) = .327$ and $p = .000$, PeP where $r(121) = -.269$ and $p = .003$, PeN where $r(121) = .398$ and $p = .000$, PeC where $r(121) = .143$ and $p = .118 > .05$, PU where $r(121) = .090$ and $p = .325 > .05$, and PEoU where $r(121) = .145$ and $p = .012$. Moreover, multiple regression results showed that the independent variables are statistically significant in predicting IoUT [$F(6, 114) = 7.517$, $p = .000$, $R^2 = .283$, and adjusted $R^2 = .246$]. I found the independent variables are significant factors that predict IT solution architects' intentions of adoption and use of CCS technology. Accordingly, I rejected the null hypothesis because the results of the study demonstrated the existence of a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with IUoT. IUoT is the measurement variable of IT solution architects' behavioral intentions to adopt and use CCS technology in Afghanistan, mainly in the main cities of Kabul, Mazar, and Herat.

Presentation of the Findings

In this study, I chose a quantitative correlational design. I collected data through an online survey questionnaire using SurveyMonkey and presented various statistical analysis proving data reliability and validity. I also used multiple regression statistical analysis to weigh the intentions of IT solution architects IUoT of CCS based on information on PeS, PeP, PeN, and PeC.

My research question and related hypotheses are:

RQ: Is there a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU with the intent to adopt CCS?

H_0: There is no relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

H_a: There is a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

To answer the research question, I collected data using a web-based survey that I administered through SurveyMonkey. I used the G*Power tool to compute the required sample size based on the effect size, error probability, power, and the number of predictors. The sample calculation indicated that a minimum of 85 respondents would provide a statistical power of 0.80, while 129 of them increased statistical power to 0.95. I gathered data from 125 IT solution architects, who responded to the survey's invitation, employed by SMEs located in Afghanistan, and completed the analysis of this study using the multiple regression method. A list of SMEs was collected from the MOCI listing 4,000 middle-sized business companies. Among those SMEs, I found 324 IT companies offering various ICT services, and most of them were located in the capital Kabul. Following approval from Walden University's IRB, a list of 204 IT registered professionals were randomly selected to participate in the survey; hence, 125 respondents make a response rate of approximately 61%. After receiving the invitation email, participants received emails every 5 days, reminding them to participate in the study for over 2 weeks until the closure of the survey.

Participant Characteristics

Descriptive statistics showed that 112 participants (93%) were men, and only 8 (7%) of them were women. In terms of the age of participants, 60% were between 25 and 34 years, while 25% were between 35 and 44. 43% of participants had at least 10 years of experience in IT, and 75% had at least 3 years of experience. 84% of participants were highly aware of CCS technology (see Table 2).

Table 2

Frequency of Demographics of Participants

Demographic	Type	Frequency	Percentage
Gender	Male	113	93.4
	Female	8	6.6
Age	18-24	7	6
	25-34	74	62
	34+	40	32
IT Experience	< 1 year	4	3
	1 - 5	23	19
	5 – 10	42	35
	10+	52	43
IT studies	< 1 year	4	3.3
	1 – 2	4	3.3
	2+	113	94.4
CCS awareness	Very High	11	9.1
	High	73	60.3
	Low	37	30.6

Instrument Characteristics

I used a VSI (see Appendix A) to collect data from IT solution architects working for SMEs in Afghanistan. I invited participants of the study based on a list of SMEs providing IT services received from the MOCI in Afghanistan. The survey consisted of 28 structured questions using a Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). Part 1 of the survey was about the demographic information of participants, including gender, age, work experience, and CCS awareness. Part 2 consisted of seven different statements from the questionnaire to determine if participants' PeS, PeP, PeN, PeC, PU, and PEoU, and IUoT.

Data Characteristics - Descriptive Statistics

The total number of respondents who answered the survey was 125. Four partially submitted surveys were discarded due to missing data, and none of the data values were corrected or adjusted. No errors in the data were identified during the data analysis. Table 3 presents a summary of data statistics description for all the survey questions, in addition to Appendix K which represents an explanatory illustration of the data through a descriptive statistics and frequencies including histograms, where a careful observation of tables' statistics and figures would provide assurance of data normality distribution and the absence of any significant skewness or kurtosis.

Table 3

Means and Standard Deviations for Quantitative Study Variables

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
MEAN.PU	121	4.00	1.00	5.00	3.5675	1.07380	1.153
MEAN.PEU	121	4.00	1.00	5.00	3.3037	.90899	.826
MEAN.PEP	121	2.50	1.75	4.25	3.3802	.51448	.265
MEAN.PES	121	3.25	1.75	5.00	3.3450	.85224	.726
MEAN.PEN	121	3.25	1.75	5.00	3.4215	.78861	.622
MEAN.PEC	121	3.75	1.25	5.00	3.5847	.77765	.605

(Table continues)

MEAN.IA	121	4.00	1.00	5.00	2.8926	.90084	.812
Valid N (listwise)	121						

Data Reliability Analysis

The first step in data analysis is to test the reliability through various analyses to ensure that the survey questions relating to the independent and dependent variables correlated to the specific construct. I performed a reliability analysis by extracting the Cronbach's Alpha of all variables of value 0.786. Cronbach's Alpha suggestive outcomes presented in Table 4 of reliability analysis. However, the comprehensive exploration of data reliability statistics can be found in Appendix H. A Cronbach's Alpha value between 0.7 and 0.9 reflects reliable measures of constructs (Clark & Watson, 1995; Taber, 2018). Table 4 of case processing summary presented 121 respondents who laid reliable and valid responses out of a total of 125 participants joined the survey. The 4 excluded records (3.2%) were partially responded; I deleted from the data set.

Table 4

Reliability Statistics and Case Processing Summary

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.786	.766	27

Case Processing Summary

		N	%
Cases	Valid	121	96.8
	Excluded	4	3.2
	Total	125	100.0

I extended this section of the reliability analysis of data and performed several tests to make sure that the questions relating to each of the variables correlated to the specific construct. I performed a reliability analysis on the set of questions of the survey and got the Cronbach's Alpha. The summary result presented in Table 5, and as a reference, the detailed analysis is depicted in Appendix H.

Table 5

Summary of Reliability Statistics Per Variable

Item	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Perceived Usefulness	.931	.939	3
Perceived Ease of Use	.760	.762	4
Perceived Privacy	.694	.698	4
Perceived Security	.824	.787	4
Perceived Connectedness	.771	.766	4
Perceived Complexity	.714	.713	4
Intention of Use of Technology	.720	.717	4

Exploratory factor analysis. In this part of data analysis, the number of variables to examine is limited to the four external constructs that are measured in the survey; PeP, PeS, PeN, and PeC. There were 32 questions in total in the survey with (a) 5 questions concerning the demographic information about the participant in PART I of the survey. In PART II, we have (b) 3 questions relating to PU, (c) 4 questions relating to PEoU, (d) 4 questions relating to PeS, (e) 4 of them relating to PeP, (f) 4 relating to PeC, (g) 4 relating to PeN, (h) and 4 questions relating to IUoT. Factor analysis can be accomplished in two steps; (a) factor extraction that involves making a choice about the type, the model, and the number of factors to extract, (b) and factor rotation comes after the factors are extracted, with the goal of achieving a simple structure in order to improve interpretability (Tarhini et al., 2016; Osborne, 2015). The KMO and Bartlett's Test (Table 6) demonstrates that the Kaiser-Meyer-Olkin measure of sampling Adequacy is 0.665 ≈ 1, indicating the suitability of data for structure detection and hence, factor analysis may be useful. Moreover, for Bartlett's sphericity tests (Table 6), the low value (sig ≈ .000 < 0.05) of the significance level confirms that factor analysis may be useful with the data. In Table J1 of total variance analysis based on Eigenvalues as shown in Appendix J, I observed four factors (see Figure 15) being identified through with an Eigenvalue strictly greater than 2.0 explaining the interrelationships among those variables. In Table J2 of rotation pattern component matrix analysis (Appendix J), I found that PeS, PeN, and PeC were correctly factored with IUoT/IA construct also, this can be explained by the nature of the questions where respondents have shown mainly a high concern about connectedness and security while their perception of complexity of CCS might mainly be tied to the bad quality of internet and the lack of security protection. Moreover, PEoU and PeP were found not correctly factored with IUoT/IA construct which can be explained the way the question is being captured and understood by respondents: “Easy access to CCS” versus “the respondent self-feeling about privacy”; For some respondents, this inquiry may have created inevitable confusion.

Table 6

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.665
Bartlett's Test of Sphericity	Approx. Chi-Square	1811.917

(Table continues)

Df	351
Sig.	.000

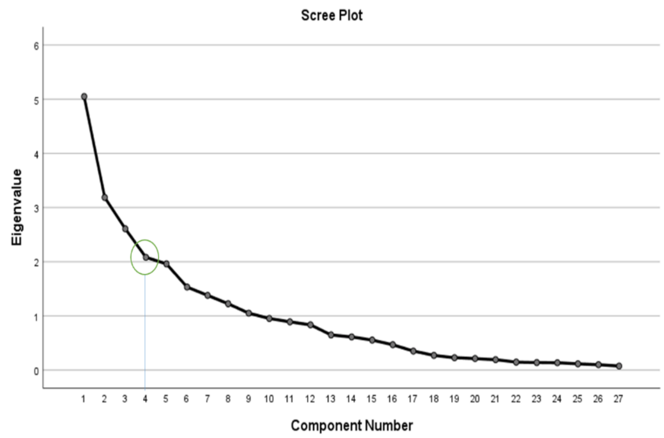


Figure 15. Eigenvalue scree plot of component number.

Test of Assumptions

In Section 2, I described several assumptions considered vital that I need to test and validate the findings of this study. The listed assumptions included the multicollinearity test, homoscedasticity, independence of residuals, normality, linearity, and outliers check. Each of these tests supports the assumptions of this study and, accordingly, I will examine every one of them.

Multicollinearity. The sample population (121 respondents) of the study was close to the minimum number of respondents (85) required. However, multicollinearity within the collected data could be an issue, and it must be checked. Both the correlation coefficient and variance inflation factors (*VIF*) are used to verify multicollinearity (Dohoo, Ducrot, Fourichon, Donald, & Hurnik, 1997). Table 5 of the Pearson Correlation among variables shows the bivariate correlation matrix and demonstrates that all bivariate correlations were less than 0.7. Dohoo et al. (1997) contended that multicollinearity could be certain at the 0.9 or higher level of a correlation coefficient. I extracted Pearson correlations to detect relationships between variables, so I examined the correlation table (see Table 7) as evidence of multicollinearity absence among the constructs. I calculated the average or the mean score of the items for a construct because multi-items measured a single construct in the questionnaire. In the table below (Table 7), the highest correlation found between the constructs was $0.357 < 0.9$. Therefore, the multicollinearity among the variables of this study was not a concern.

Table 7

Bivariate Correlation Scatterplot Matrix

		MEAN.PU	MEAN.PEU	MEAN.PEP	MEAN.PES	MEAN.PEN	MEAN.PEC	MEAN.IA
MEAN.PU	Pearson Correlation	1	.062	-.086	.180*	.211*	.336**	.129
	Sig. (2-tailed)		.501	.349	.049	.020	.000	.160
	N	121	121	121	121	121	121	121
MEAN.PEU	Pearson Correlation	.062	1	.190*	-.062	.172	.015	.018
	Sig. (2-tailed)	.501		.037	.496	.060	.871	.844
	N	121	121	121	121	121	121	121
MEAN.PEP	Pearson Correlation	-.086	.190*	1	-.241**	-.179*	.115	-.271**
	Sig. (2-tailed)	.349	.037		.008	.050	.207	.003
	N	121	121	121	121	121	121	121
MEAN.PES	Pearson Correlation	.180*	-.062	-.241**	1	.209*	.241**	.249**
	Sig. (2-tailed)	.049	.496	.008		.022	.008	.006
	N	121	121	121	121	121	121	121
MEAN.PEN	Pearson Correlation	.211*	.172	-.179*	.209*	1	.344**	.357**
	Sig. (2-tailed)	.020	.060	.050	.022		.000	.000
	N	121	121	121	121	121	121	121

(Table continues)

MEAN.PEC	Pearson Correlation	.336**	.015	.115	.241**	.344**	1	.125
	Sig. (2-tailed)	.000	.871	.207	.008	.000		.172
	N	121	121	121	121	121	121	121
MEAN.IA	Pearson Correlation	.129	.018	-.271**	.249**	.357**	.125	1
	Sig. (2-tailed)	.160	.844	.003	.006	.000	.172	
	N	121	121	121	121	121	121	121

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Furthermore, the *VIF* is a transformation of the R^2 resulting from predicting an *X* variable by other predictors in the model (Salmerón, García, J., García, C., & del Mar López, 2018). *R* is the multiple correlation coefficient; then, there is a form of relationship between the two concepts of variables correlation and *VIF*; Knowing that *VIF* = 1/*tolerance* so the minimum tolerance analysis is as well used to identify the multicollinearity (Disatnik & Sivan, 2016).

For further testing the multicollinearity, I measured the minimum tolerance analysis of the independent variables. Independent variable tolerance explains the level of the variability influenced by other predictor variables, so a value that is less than 0.1 may indicate multicollinearity (Disatnik & Sivan, 2016). In below Table 8 (Table L3 of Appendix L of Multiple Regression Analysis), I found tolerance values of .824 for PeP (*VIF* = 1.213), .833 for PeS (*VIF* = 1.200), .846 for PeN (*VIF* = 1.182), and .729 for PeC (*VIF* = 1.372) indicating complete absence of any multicollinearity among variables. All *VIF* = 1/*tolerance* values for PU, PEoU, PeS, PeP, PeC, and PeN are by far lower than 10, supporting the complete absence of any multicollinearity among the constructs of study.

Table 8

Unstandardized Coefficients, Correlations, and Collinearity Statistics

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.720	.474		5.736	.000	1.781	3.660					
	W_PEP	-.266	.101	-.230	-2.638	.010	-.466	-.066	-.269	-.240	-.209	.824	1.213
	W_PES	.151	.060	.218	2.504	.014	.032	.271	.327	.228	.199	.833	1.200
	W_PEN	.209	.058	.311	3.611	.000	.094	.324	.398	.320	.286	.846	1.182
	W_PEC	.020	.077	.025	.265	.791	-.132	.173	.143	.025	.021	.729	1.372
	W_PU	-.023	.053	-.036	-.425	.672	-.128	.083	.090	-.040	-.034	.855	1.170
	W_PEU	.155	.072	.179	2.169	.032	.013	.297	.145	.199	.172	.918	1.089

a. Dependent Variable: W_IA

Outliers, normality, and linearity. A normality test examines the sample data, whether or not it represents a normally distributed population. A normality test can be done by the Kolmogorov – Smirnov (K-S) test and Shapiro – Wilk (S-W) test (Hu, Yu, & Wang, 2016). Data may not be normally distributed if the significance (*sig*) value is too close to zero; otherwise, it is assumed that customarily distributed (Hu, Yu, & Wang, 2016). Table 9 below shows the *p-value* of significance for PeP, PeS, PeN, and PeC are respectively of $p < 0.5$ for both KS and SW test outcomes, which indicates that we may, or may not, face a normality issue with our data distribution.

Table 9

Tests of Normality of K-S & S-W

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MEAN.PU	.285	121	.000	.841	121	.000
MEAN.PEU	.168	121	.000	.928	121	.000
MEAN.PEP	.202	121	.000	.926	121	.000
MEAN.PES	.104	121	.003	.961	121	.001
MEAN.PEN	.299	121	.000	.873	121	.000
MEAN.PEC	.125	121	.000	.973	121	.015
MEAN.IA	.154	121	.000	.953	121	.000

a. Lilliefors Significance Correction

Moreover, relying on different reliable statistical methods, I estimated the normality pattern, outliers and linearity, and homoscedasticity by exploring the normal probability plot of the regression standardized residual shown in Figure 16 below, the histogram of the standardized residuals presented by Figure 17, and finally the scatterplot of standardized residuals illustrated by Figure 18. Using PP histograms and graphical representations to observe specific pattern of a collected data distribution of a random sample of a population, is a common practice of most researchers who can easily visualize and assess the existence of an outlier and decide about normality pattern (Koszalinski et al., 2018; Kumari & Kennedy, 2017). Figures 16, 17, and 18 of standardized residual analysis about normality, the output pattern that I observed was that some of the variables slightly deviated from the desired normality pattern, however, such normality deviation was not significant and the data still can be treated as normally distributed. In Figure 16 of the normal probability plot (P-P) of the regression standardized residual, I observed that the data is normally distributed around the diagonal axis with insignificant deviation.

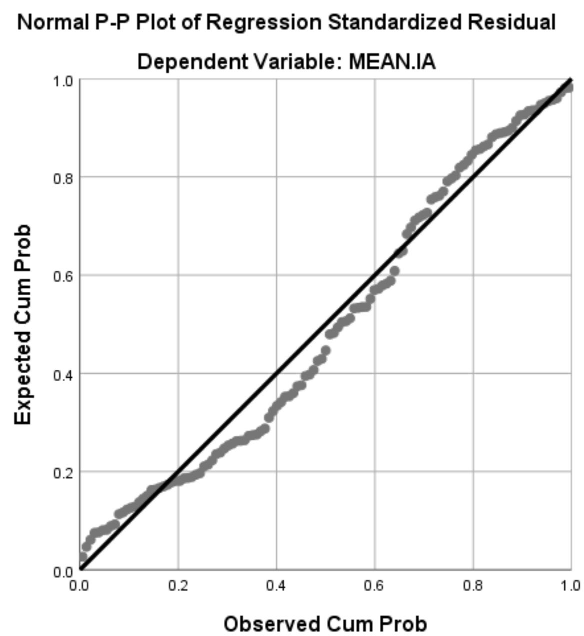


Figure 16. Normal PP of the regression standardized residual.

The examination of Figure 16 designated that no significant violations of the assumptions. The leaning distribution of the points around the center axis specified that violations of the assumption of normality were not present and that significant outliers were nonexistent. In Figure 17 representing a distribution histogram of the regression standardized residuals, the symmetric bell-shaped histogram distributed around zero indicates a valid normality assumption; hence, the slight left deviations that appear in the figure are not significant and provided no skewness impact on the shape of the bell-curve. The histogram observation as well confirms that normality was not a concern.

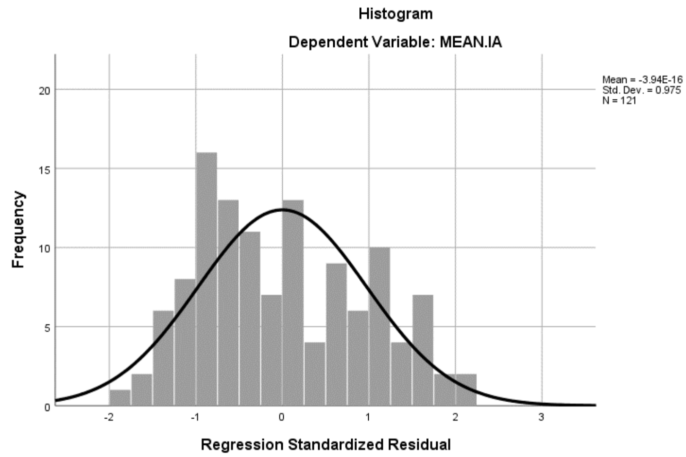


Figure 17. Histogram of the regression standardized residual.

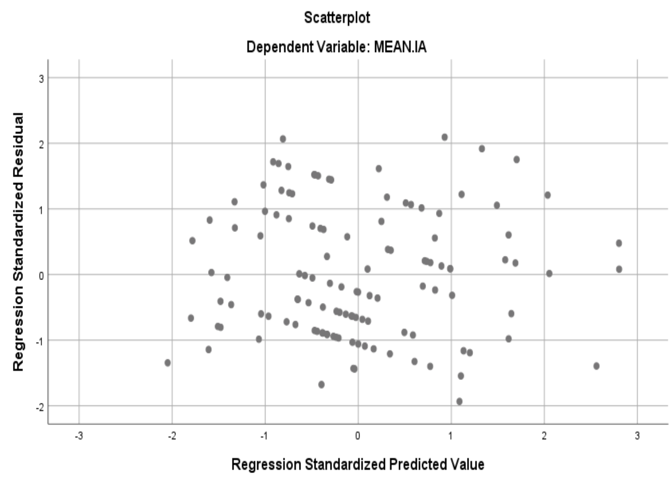


Figure 18. Scatterplot of the standardized residuals.

In the scatterplot of the standardized residuals (Figure 18), it is noticeable that dots are forming a rectangle middle of the plot, and hence the absence of a regular pattern reinforced that the assumptions were being satisfactory.

Furthermore, and according to Auffermann, Ngan, and Hu (2002), as well as Gómez, Gémar, Molinos-Senante, Sala-Garrido, and Caballero (2017), a bootstrapping test can help evaluate the impact of outliers. Hence, I used the bootstrapping technique to identify the influence of assumptions' violation by generating a bootstrap regression of 2,000 random samples to certify a reliable and robust estimate of variables. In this bootstrap test, I used a confidence interval of 95% to extract (*p*) values while avoiding any normality assumption related to the (*t*) distribution used in the standard linear regression. Table K2 of Appendix K (Bootstrap extraction of Pearson correlations) the statistical values of the variables vary between the upper and lower values of the means and medians, and the distances of standard deviation upper and lower values were insignificant.

Moreover, I analyzed the skewness and kurtosis values of the data looking after any normality issue (Table 10). To estimate normality, the values thresholds for skewness and kurtosis are respectively ±3 and ±10 (Bono, Blanca, Arnau, & Gómez-Benito, 2017). After analyzing the normality test results, the values of each variable's skewness and kurtosis test result came within the advised measures of normality. Table 10 presenting a descriptive statistical computation of skewness and kurtosis, demonstrated that the skewness values of the variables PeP, PeS, PeN, PeC, and IA varied from -.832 to .631 (-3 < -.832, .631 < +3), and the kurtosis test values varied from -.763 to 1.034 (-10 < -.763, 1.034 < +10) for the same variables.

Table 10

Descriptive Statistics of Skewness and Kurtosis

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
MEAN.PU	121	1.00	5.00	3.5675	1.07380	-.832	.220	-.575	.437

(Table continues)

MEAN.PEU	121	1.00	5.00	3.3037	.90899	-.566	.220	-.430	.437
MEAN.PEP	121	1.75	4.25	3.3802	.51448	-.739	.220	1.034	.437
MEAN.PES	121	1.75	5.00	3.3450	.85224	-.175	.220	-.722	.437
MEAN.PEN	121	1.75	5.00	3.4215	.78861	.631	.220	-.713	.437
MEAN.PEC	121	1.25	5.00	3.5847	.77765	-.383	.220	-.242	.437
MEAN.IA	121	1.00	5.00	2.8926	.90084	.320	.220	-.763	.437
Valid N (listwise)	121								

Therefore, the collected data were considered normal, respecting all assumptions, and there was no need for any transformation. As per Barker and Shaw (2015), the insignificant defilement from the expectedly desired assumptions would be permitted, and therefore the survey efficiency is confident as long as the size of the sample is bigger than 100 participants. However, this study of sample size as large as 121 respondents, the Pearson's correlation coefficient analysis and multiple linear regression analysis may allow slight deviances from the expected normality assumptions and would be treated as appropriate.

Homoscedasticity. Homoscedasticity, as explained in the previous section, means that the variance around the regression line is similar for all values of the independent variables. A Durbin Watson value of 2; means that there is no correlation between the independent variables (Alao et al., 2016). In Table 11, the Durbin Watson value is 1.909 ≈ 2, confirm that there exist no worries of correlation among residuals, which indicated that the homoscedasticity assumption was met.

Table 11

Model Summary Durbin-Watson Test

Model	R	R2	Adjusted R2	Std. Error	D-W
1	.532	.283	.246	.60012	1.909

Inferential Results

In this study, I used a standard multiple linear regression of α = 0.05 two-tailed. With the multiple linear regression, I wanted to examine the effectiveness of PeS, PeP, PeN, PeC, PU, PEoU in predicting the IUoT of the IT solution architects. The independent variables were PeS, PeP, PeN, PeC , and the dependent variable was IUoT. The null hypothesis and alternative hypothesis were:

H_0: There is no relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

H_a: There is a relationship between IT solution architects' PeS, PeP, PeN, PeC, PU, and PEoU and intent to adopt CCS.

According to Table 11, the model framework was able to significantly predict the behavioral intention of adoption and use of CCS in Afghanistan, $F(6,114) = 7.517$, *p_value* = .000, *and* $R^2 = .283$. The R^2 value indicated that the model could explain 28% of the total variability in behavioral intention. The coefficients representation in Table 12 showed that the external independent variables of PeS, PeP, and PeN were statistically significant with PeN ($t = 3.611$, $p < .000$). PeN is presented as the highest contributor to the prediction of CCS' intention of adoption than the other two significant contributors of PeS and PeP presented respectively with a statistical significance model of (t = 2.504, p < .014) and (t = -2.639, p < .010).

Table 12

Coefficients Presentation for the Final Predictive Equation

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
1	(Constant)	2.720	.474		5.736	.000			
	W_PU	-.023	.053	-.036	-.425	.672	.090	-.040	-.034
	W_PEU	.155	.072	.179	2.169	.032	.145	.199	.172
	W_PEP	-.266	.101	-.230	-2.638	.010	-.269	-.240	-.209
	W_PES	.151	.060	.218	2.504	.014	.327	.228	.199
	W_PEN	.209	.058	.311	3.611	.000	.398	.320	.286
	W_PEC	.020	.077	.025	.265	.791	.143	.025	.021

a. Dependent Variable: W_IA

The final predictive equation based on the predictor variables was:

$$IUoT = 2.720 - (.266\ x\ PeP) + (.151\ x\ PeS) + (.209\ x\ PeN) - (.020\ x\ PeC)$$

Perceived security. PeS has a positive slope of 0.151 (p < .05), indicating that for every degree of increase in PeS, there is an increase of .151 in the behavioral intention of adoption (IUoT). The squared semi-partial correlation coefficient (sr^2) was .199; indicating that 20% of the variance in the behavioral intention of adoption is based on PeS in case the other variables of PeP, PeC and PeN are controlled.

Perceived privacy. PeP has a negative slope of (-.266, p < .05) which as well indicates that for a point of increase in PeP, there is in turn -.266 decrease of points in the behavioral intention of adoption. The squared semi-partial correlation coefficient, sr^2, for

PeP was -.209, which indicates a 21% of the variance of the behavioral intention of adoption is based on PeP in case the other independent tested variables are controlled.

Perceived connectedness. PeN has a positive slope of .209 (p < .05), indicating that for one point of increase in PeN, there is .209 point of increase in the behavioral intention of adoption. The squared semi-partial correlation coefficient, sr^2, for PeN was .286, which indicates a 29% of the variance of the behavioral intention of adoption is based on PeN in case the other independent tested variables are controlled.

Perceived complexity. PeC has a positive slope .020 with a degree of significance of p = 0.791. Despite the slight slope of PeC, the variable is not a significant predictor of IUoT because its (p) is greater than .05. Such statistical result means that for every point of increase in PeC, one may or may not predicts .020 points (2%) of increase in IUoT.

Analysis summary. The objective of this study was to demonstrate the level of efficiency of PeS, PeP, PeN, PeC to predict IUoT of IT solution architects to use CCS. I used the standard multiple linear regression analysis methods to examine the effectiveness of the predictor variables. I evaluated the assumptions adjoining multiple regression and found that no violations were to exist. The model was able to significantly predict behavioral intention of adoption of cloud services; $F(6,114) = 7.517$, $p = .000$, and $R^2 = .283$. However, out of the four predictor variables of the study, three of them, PeS, PeP, and PeN were able to provide suitable predictive information about the IUoT. The findings in this study rejected the null hypothesis showing that PeS, PeP, PeN, and

PeC can predict the behavioral intention of IT solution architects in Afghanistan to adopt and use CCS. More accurately, the three constructs of PeS, PeP, and PeN were associated with the behavioral intention of adoption of CCS, whereas PeC did not significantly predict IUoT.

Theoretical conversation on findings. I used the TAM model as the theoretical model of this study developed by Davis (1989). As shown in section 1, Fred Davis developed this model relying on two core constructs of PU and PEoU as instrumentation to predict users' acceptance of computers. The framework was enhanced later on by Davis and Venkatesh (2000) by adding another construct the behavioral intention of use. Valtonen et al. (2015) demonstrated that TAM theory is used to measure attitudes and reasons behind technology adoption. Mortenson and Vidgen (2016) demonstrated the constructs' relationship of the TAM is mainly evolving from semantic relationships between its questionnaire items; however, ETAM of this study was developed by adding external variables of PeS, PeP, PeN, and PeC constructs to the model. The results for the validity (VIF > 0.50) and reliability (Cronbach $\alpha = 0.786$) tests indicated that the ETAM model was relevant to measure PeS, PeP, PeN, PeC, PU, and PEoU of solution architects' behavioral intentions of use of CCS in Afghanistan.

After data collection from the IT solution architects in Afghanistan and the multiple regression statistical analysis applied, I demonstrated that the model framework could predict IUoT of CCS. Precisely the model confirmed that the construct of PeN scored as the most significant predictor of IUoT, the second significant predictor after was PeS, and the third significant predictor was PeP. However, the predictor PeC was not a significant predictor of IUoT. The validity, reliability, and inferential analysis results supported the arguments from Davis et al. (1989), Davis and Venkatesh (2000), Dutot (2015), and Sharma et al. (2016); that the TAM model is appropriate to measure IUoT. As discussed in section 2, that Changchit and Chuchuen (2016), Gangwar et al. (2015), and Hsu et al. (2014) found positive associations between behavioral intentions to adopt a technology and the external variables PeS, PeP, and PeN; therefore, in this study, the regression test analysis supported Changchit and Chuchuen (2016) and Gangwar et al. (2015) findings that PeN is the highest predictor of intentions while PeS and PeP have relatively lower effects.

In Section 1 and Section 2, I discussed the application of the model theory of TAM in several studies to address interrelationships between external variables on the core construct of the model theory framework. The ETAM System theory was used as the basis for proposing a model theory construct as the theoretical foundation to understand the influence and impact on decision making to adopt cloud computing technology (Davis, Bagozzi, & Warshaw, 1989; Dutot, 2015; Sharma, Al-Badi, Govindaluri, & Al-Kharusi, 2016). The outcome of findings supported what Ishola (2017), in his study of TAM, showed that the PeN construct and PeS/PeP were key barriers affecting the fast adoption of cloud computing services by SMEs in Nigeria. As well, Obinkyereh (2017), based on the TAM model framework, demonstrated that PeN and PeS are the highest contributors to the intention of cloud computing adoption in Ghana. Harmon (2018) demonstrated that security strategy is an indispensable construct for an appropriate implementation of operating cloud computing services. The analysis findings supported the literature of the study that, based on the ETAM model, the behavioral intention of adoption of cloud computing is significantly predictable using specific external predictors:

Perceived usefulness. The result of the findings indicated that there was an insignificant bond between cloud computing decisions of adoption by solution architects in Afghanistan and PU. This finding is contrary to the findings of Davis (1989) and Dawson (2015). Davis (1989) contended that PU is a strong indicator of decision-makers' willingness to adopt and use a particular service of information technology. Dawson (2015) used PU to determine cloud computing adoption in higher education in the USA. Obinkyereh (2017) also used PU to determine cloud computing adoption by SMEs in Nigeria. Both Dawson (2015) and Obinkyereh (2017) found that PU significantly determines cloud computing adoption. This study finding determined that PU was an insignificant contributor to cloud computing adoption, as it accounted for 2.3% of the variance of cloud computing adoption in Afghanistan. The p_value = 0.672 was far bigger to meet the statistical significance criteria ($p < .05$). Such a statistical result of significance for perceived usefulness implied that for any association that might exist between perceived usefulness and cloud computing adoption decision could be a coincidence due to a chance. Solution architects in Afghanistan had perceived that cloud computing could not enhance employees' task performance of the SMEs; neither could improve the work environment and increase productivity.

Perceived ease of use. The results specified that there was a significant relationship between cloud computing and PEoU. Such a result implied that there was a significant affiliation between PEoU and cloud computing adoption decisions by solution architects in Afghanistan. The result confirmed the findings of Davis (1989) and Dawson (2015). The finding is contrary to Obinkyereh (2017) findings of his study of cloud computing adoption in Nigeria. Obinkyereh (2017) found an insignificant influence of PEoU on cloud computing adoption by SMEs in Nigeria. The analysis of this study demonstrated that PEoU accounted for 16% of the variation in cloud computing adoption in Afghanistan. The result showed that solution architects in Afghanistan agreed that PEoU would influence cloud computing adoption in Afghanistan. Such a finding implied that solution architects in Afghanistan perceived cloud computing would be useful and effortless to learn, and employees of SMEs could easily get familiar with CCS.

Perceived security. This study's findings supported prior studies of Obinkyereh (2017) and Dawson (2015) that PeS was a significant, influential factor of cloud computing technology. Previous studies, as well, found that PeS has a negative influence on cloud computing adoption (Bokefode, Swapnaja, Subhash, Kailash, & Sulabha, 2015; Singh et al., 2016). Findings indicated that PeS might account for 20% of the variation in cloud computing adoption in Afghanistan. Such a result infers that solution architects in

Afghanistan approved that cloud computing security could influence CCS adoption in Afghanistan.

Perceived connectedness. The findings of this study implied that there is a significant association between PeN and cloud computing adoption by solution architects in Afghanistan. The respondents of this study designated that the Internet's PeN is a factor that might determine the CCS adoption in Afghanistan. Büchi, Just, and Latzer (2016) suggested that bridging the digital divide increases access to the internet with significant focuses on factors such as PeN and related services and that inevitably would lead to an increase in CCS adoption. This finding also confirms (Abou-Shouk et al., 2016; Obinkyereh, 2017; Tan et al., 2018) other studies findings that the Internet's PeN influence information technology and CCS adoption. The results indicated that PeN might account for 29% of the variation in CCS adoption in Afghanistan. The study implied that solution architects in Afghanistan approved PeN could influence the cloud computing adoption in Afghanistan.

Perceived privacy. The findings showed that there is a significant correlation between PeP and cloud computing adoption by solution architects in Afghanistan. The participants of this study determined that PeP is a factor of influence on cloud computing adoption decisions in Afghanistan. Previous studies (Dawson, 2015; Ishola, 2016; Khan & Al-Yasiri, 2016; Obinkyereh, 2017; Raza et al., 2015; Zhou et al., 2017) demonstrated that both PeS and PeP as factors of information protection had significantly influenced information technology services as well as CCS adoption. Sicari et al. (2015) contended that there is a thin separator between security and privacy, and hence for some security professionals, it is difficult to define significant differences between both factors. In this study's questionnaire instrument of data collection, I made it clear that privacy is meant to be the users' profile and personal information as well as customers' profiles and personal information (see Annexure A, Part II). This study's findings indicated that perceived privacy might account for 27% of the variation in cloud computing adoption in Afghanistan. Such a result infers that solution architects in Afghanistan agreed that cloud computing security could significantly influence the cloud computing adoption in Afghanistan.

Perceived complexity. The analysis demonstrated that PeC had a shallow influence on solution architects' cloud computing adoption decisions in Afghanistan. PeC had a statistical value of significance much higher than the threshold ($p < .05$) and hence, did not meet with the criteria of the statistical significance. Previous studies (Gutierrez et al., 2015; Pedone & Mezgar, 2018; Phaphoom et al., 2015; Shiau & Chau, 2016) demonstrated that PeC is a significant factor of influence for information technology as well as cloud computing adoption. I discussed in section 2 that Phaphoom et al. (2015) and Pedone and Mezgar (2018) associated complexity of cloud computing services to several phenomena such as IT infrastructure architecture, integration with current systems, data migration, operational processes, and security setup. This study's findings indicated that PeC might account for 2% ($p = 0.791 >> .05$) of the variation in CCS adoption in Afghanistan. Such a result infers that solution architects in Afghanistan agreed PeC could not influence the CCS adoption in Afghanistan. Such a statistical result of significance for PeC implied that any association that might exist between PeC and CCS adoption decision could be a coincidence due to a chance.

However, this study's differences in findings from other previous studies, resulting of PU and PeC insignificant influence on cloud computing adoption, might be attributed to many facts related to the particular case of the location where security posture was always at risk, was lacking infrastructures such as high availability internet and consistent electrical power, in addition to a complete absence of IT policy and clear regulations about information privacy and security. Such an environmental gap in the country's infrastructure might be the reason behind solution architects losing beliefs that PU could contribute effortlessly to improve the employee work environment while ecosystem services suffer continuous and unpredictable instability and lots of outages. Moreover, solution architects' PeC showed a fainted influence might be due to the complete absence of IT policy where ISP and CSP do not have any SLA or KPI obligations, so the CCS ecosystem specific intricacy in Afghanistan might have impacted the feedback of respondents. Moreover, the predominant influence of the Internet PeN on IUoT over PeP and PeS might be an indicator of IT solution architects' anguish from the absence of reliable Internet connectivity. Another essential aspect that might affect participants' perception of CCS technology is the customer experience with regards to technology efficiency and service consistency, which directly is linked to the lack of infrastructure and regulations.

Applications to Professional Practice

This study was designed to examine the correlation between PeS, PeP, PeN, PeC with the behavioral intention of IT solution architects to adopt and use CCS in Afghanistan. The results of this study will allow IT leadership, managers, and solution architects as decision-makers to have a better awareness of the challenges and barriers that may slow down CSP in the country, providing access to CCS. Moreover, the findings of this study may positively influence the decision of IT managers to deploy the right IT strategy before the adoption of CCS.

It is ostensible, based on the data collected, that IT solution architects in Afghanistan are influenced by their technical environment of internet availability when deciding to use cloud computing solution services. The environmental impact would mean that IT architects highly regarded the necessity of good Internet infrastructure on both sides of the key performance of availability and reliability. IT architects, according to concerns revealed through the survey, were interested in diminishing the amount of end-user efforts and frustrations that stem from using new technology.

In addition to PeN, the IT architects understood the impact of other factors on the quality of service of CCS. PeS was the second biggest contributor to predicting the behavioral intention of adoption of technology, indicating that a clear security framework and strategy was needed to be more positive to accept deploying their owned data on remote storage in a cloud computing facility.

PeP, as well, showed a similar influence to predicting IUoT, with a negative slope indicating less interest to adopt CCS every time privacy is enhanced. PeP is factored with PEoU, which measured the personal feelings toward the easiness of daily tasks because IT architects may have connected the *end-user* privacy tightly to his everyday use of the IT resources on the cloud. So, any perceived improvement in privacy protection strategy had a reversed influence on PEoU. Such negative feeling may be due to the untrusted regulations if existed, and the commitment of professionals to the law of information technology.

PeC was not significant in predicting, and this may be due to IT architects not knowing what type of complexity CCS is about, especially that CCS has not been experienced and is not of heavy use in Afghanistan as of yet. This study addressed problematic factors, of connectedness, security, and privacy, were treated as main barriers slowing down the progress of CCS, may have been perceived as essential components of an end-to-end CCS ecosystem and treated as main factors of the complexity of the CCS solution.

PU as well was not statistically significant in predicting the intentional behavior of adoption of CCS, and this may be due to IT architects not being business savvy people and not knowing how beneficial CCS is for business performance from an end-user productivity point of view. At the time of the study, the subject of cloud computing remote services was novel in Afghanistan and was still a new product that had not been massively used in the country by the SMEs yet. Moreover, participants may have connected the usability of the CCS to the absence of the key factors of a reliable solution that only can be accepted once the Internet, security, and privacy issues are resolved.

Moreover, the CCS usefulness may have tremendously been affected by the data storing status, that IT architects valued the criticality of having their data stored away without their direct control and challenges that they may face afterward with the absence of a clear IT policy and lack of regulations concerning privacy and data protection. In data analysis, the IT architects disclosed that if they had not have faced the ambiguity of privacy and security, they would become more prone to use CCS.

PEoU was statistically a good predictor of IUoT because IT architects may have realized CCS is an OnTheShelf product with an immediate provisioning mechanism and high reachability performance, and despite their negative perception about the internet, privacy, and security their PEoU remained as a mediator positively factored with IUoT.

The overall outcome of this study, the implementation of CCS in Afghanistan and its adoption by IT architects who influence the decision making, depends on how they can inform IT managers and leadership, being end-users of the technology, of the benefits and returns of the CCS to their businesses. The internet connection to cloud computing services was the major barrier preventing IT architects from accepting CCS as a reliable solution. Security and privacy were a concern of some of the participants that slowed down the deployment of CCS. IT architects may have to incorporate an intermingled end to end CCS ecosystem solutions to alleviate the impact of the absence of reliable internet connectivity and security/privacy regulations. The study showed that both perceived complexity and perceived usefulness did not influence CCS positive decision making.

Implications for Social Change

This study was done to recognize if four external constructs, namely PeS, PeP, PeN, and PeC, were able to predict the behavioral intention of adoption and use of the CCS technology by the IT architects in Afghanistan. The results of the study showed that PeP, PeS, and PeN could predict the behavioral intention to use CCS technology. Knowing this information, the Ministry of communication and information technology (MOCIT) can take steps to increase efforts to revamp the IT fiber infrastructure design to increase service connectivity availability and eliminate the constant interruptions. Moreover, MOCIT and the Afghan Telcom Regulatory Authority (ATRA) can issue an IT policy that includes the *end-user* rights of IT service performance protocol, information privacy, and the least security framework setup required for the essential protection of the information. MOCIT and ATRA can organize as well several educative seminars of awareness to tutor IT professionals about their rights concerning the information protection of individuals, information privacy for companies and *end-users*, and the current mechanisms and best practices used to secure data platforms from any unauthorized access. Moreover, ATRA can extend steps to encourage the Ministry of justice to decree IT security and privacy breach and verdict a minimum SLA requirement for IT services in the sense of protecting the IT services consumers.

In using reliable CCS with high quality, IT solution architects might encourage selling unfailingly the idea of CCS to SMEs who maybe are in bad need for IT resources to enhance their business performance. CCS will allow SMEs in Afghanistan to use vital services for business such as domain exchange to brand their platform of communication instead of using public media like Hotmail, Gmail, as well as on-the-shelf business solution applications like supply chain, payroll, accounting, customer relationship management, Enterprise resource planning and alike. CCS high performing services would facilitate the tasks of their employees and increase the productivity of services of most SMEs and bring most of the benefits that cloud computing can provide to a business.

Recommendations for Action

In this study, I used an enhanced TAM model to examine four constructs of my choice, namely PeS, PeP, PeN, and PeC were able to predict the intention of IT architects in Afghanistan to adopt and use CCS, which were still treated as novel technology in the country. This study has various benefits for SMEs and, ultimately, for banking, financial institutions, and education services that need to rely indispensably on a reliable CCS to increase business efficiency.

The study can be accessed and reviewed by MOCIT and ATRA whose employees and decision-makers influence the government development strategy, IT alliances and communities who can influence the minister of telecommunication and the head of ATRA as well as ministry of education and concerning intuitions and offices to improve distant studies and online education, IT managers and leaders of SMEs in public and private sector, and IT architects of ICT SMEs who participated in the survey and wanted to learn from the outcome and findings of the study. ATRA should implement effective IT and CCS policy, which would stem from a global IT policy and regulations.

The IT architects of SMEs in Afghanistan can effectively adopt IT services hosted on the global cloud by developing, through IT alliances, an IT strategy for CCS that leverage basic requirements of the Internet, security, and privacy. The CCS strategy should encompass a clear description of the benefits and return of CCS on business performance and agility as well as employees' productivity.

Once an IT policy is issued, ICT organizations should respond to Internet instability, security threats, and unprotected data privacy problems associated with IT *cloud-hosted* services by educating and encouraging SMEs to deploy corporate policy governance. ATRA should organize educative events and training, which focuses on the three findings key elements to IT professionals to take appropriate actions to ensure that SMEs, ISPs, and CSPs comply with such a policy for it to be more efficient. The three key elements were reliable internet connectivity, appropriate data security, and the protection of information privacy.

My first recommendation was that the IT policy should oblige ISPs and CSPs to regard these three vital elements as the necessary infrastructure delivery KPIs with an acceptable SLA commitment that the policy may describe. My second recommendation was that IT architects should provide their customers with a CCS policy template and awareness to help CIOs and IT directors build an appropriate framework of service monitoring and availability governance. My third recommendation for action was that IT architects should balance their IT solution technical proposal by adding an IT operational framework requirement and governance section to improve compliance with IT policy, avoid hindering the CCS consumers' expectations, and gather the solution key players; ISP, CSP, IT architects, and Customer to provide an IT service with acceptable KPIs for a performing business.

Recommendations for Future Study

This study is subject to some limitations. First, I recruited participants based on the MOCI list of the registered ICT SMEs to solicit their IT architects about CCS behavior intention. Hence, the relevance of the population relies on business types, some limitations of the MOCI list, and some IT architects that may consider as CSP resellers and have had some influence on the participants' characteristics. In addition to that, the prompted participants' CCS behavioral intention of adoption was not observed, so maybe there is a possibility of bias between daily monotonous behavioral intention and the self-reported behavior; yet, Walden IRB confirmed the sample population requirements compliance as related to the data collection. Second, the study reckoned on the geographic location of the participants, on their registered organizations, and the classification of the organizations as SMEs specialized in ICT for which participants worked as IT architects. According to above, I collected the data of the study from some

IT architects' respondents and employees working for some ICT organizations in the main cities of Kabul, Mazar, and Herat at the time of the data collection.

Further studies are required to investigate the correlation between the constructs of the TAM model and the behavioral intention to adopt CCS relying on inputs from different populations of the same or other geographical regions of Afghanistan. Further research is required assuming that infrastructure performance in Afghanistan may significantly improve, especially the internet, and that the perception of IT architects about CCS as a novel technology may significantly change after they internalize what their customers expect from them and experience the outcome of the technology on end-users. Hence, in the future, researchers could examine if perceived connectedness, security, and privacy could affect the behavioral intention of the findings of this study. Moreover, despite the success of this study of TAM demonstrating the relationship between the constructs and the behavioral intention, few types of research of study applied for Afghanistan; hence, some avenues remain for future research. Researchers could conduct future research using a qualitative method to examine the behavior intention in association with the actual use of consumers' CCS as well as IT architects' perception of external factors that remained as barriers to technology penetration. Also, in the future, researchers could use other models of study such as UTAUT2 or TAM2 to examine how IT CCS behavior adoption, under the same circumstances and condition of constructs perception, evolves over an extended period and demonstrate whether CCS behavior intention of adoption may or may not influence the behavior of use of technology. Future researchers may rely on population CCS adopters with better infrastructure functionality and other CCS adopters with a nonperforming infrastructure of the internet, security, and privacy and examine the influence of constructs on behavior intention and can analyze the changes of the efficient behavior of use between both categories. Finally, future researchers can use this research to validate the descriptive and instructive structure of the findings by using other categories of participants, different sample sizes, different geographic areas, and various research designs.

Reflections

I had a great learning experience in research methodologies at Walden University. Most times, I was annoyed by several demands, where I had to entice my beliefs and to withstand resilient, especially due to revisions and recommendations that I felt are hectic, slowing down my advancement throughout the journey to complete my doctoral study. My journey of the study was extremely prolific as I expanded my knowledge about the topic and my understanding of the fundamentals, namely the multifaceted aspect of CCS technology and various theories of technology acceptance I elaborated about in the study.

Although I deepen my understanding of different research approaches, however, I expanded my knowledge of quantitative research with various designs. When I started this mission of study, I did not have any sound understanding of the TAM model, and the intelligent way novelists created the various constructs and predictors of the intentional behavioral of adoption of technology. I developed my knowledge through the different phases of the project that my Chair of study and mentor had taken me through, and by reading many articles of peer-reviewed research on the same or similar theoretical model. I acquired an exhaustive understanding of TAM and its association with the intentional behavior of adoption and use of CCS as an IT technician.

It is without any preconceived bias that I started this study to examine the level of significance of the correlation between the IT architect’s IUoT, PEoU, PU, PeP, PeS, PeN, and PeC. The outcome of the study demonstrated that PEoU, PeP, PeS, and PeN influence positively IT architects’ intention to adopt CCS in Afghanistan. The findings of this study provide some indications to IT architects to improve their CCS solution architecture, to CIOs and IT managers to adopt an IT policy and CCS strategic framework, to the regulatory body to accommodate an IT policy that protects IT consumers, and as well can inspire future researchers.

Summary and Study Conclusion

I conducted quantitative correlational research-based on a nonexperimental design. The survey’s participants were employed online to analyze the level of significance of the relationship between the external factors of perceived privacy, perceived security, perceived connectedness, and perceived complexity with the IT architects’ behavior intention of adoption of cloud computing services in Afghanistan. I used an enhanced predictive TAM framework and an online pretested survey instrument to achieve the purpose of this study. I collected the data using a survey that I built on SurveyMonkey with direct online access for the participants of the study. I started the data collection phase by sending out 208 surveys’ invitation through emails, and I sent around 424 reminders over two weeks. I received 125 responses, among which, four surveys were incomplete that I discarded them. The response rate was 61%. The collected data were exported from SurveyMonkey and uploaded into SPSS tool of IBM version 25. Using SPSS, I executed the frequency and descriptive statistics, reliability, and validity analysis of the assumptions, Pearson's correlation, and multiple regression analysis to test the hypothesis of the study.

The analysis of the statistical results allowed the null hypothesis rejection. I found that perceived privacy, perceived security, and perceived connectedness had a stronger positive impact on IT architects' behavioral intention to adopt CCS, while perceived complexity had an insignificant positive effect. Moreover, I found that perceived connectedness was the top leading key driver of CCS intention of the adoption of the IT architects. I found perceived security to be the second of the constructs with a stronger positive impact on the IT architects' and perceived privacy was the third contributor of influence on IT architects' behavior intentions. Despite some limitations in the design of this research, IT architects and IT leaders can use the findings and make informed decisions on how to develop better strategies to adopt reliable solutions for cloud computing services. The purpose of this research of study was to use the four key external factors of privacy, security, connectivity, and complexity with the TAM model to measure their influence on IT architects' behavioral intentions. The findings of the analysis allowed to provide the IT heads of the SMEs in Afghanistan the sound technical and operational ground to develop better IT solutions for their companies based on cloud computing services.

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Appendix A: Data Collection Instrument

QUESTIONNAIRE OF SURVEY INSTRUMENT OF STUDY

Topic: Cloud computing adoption in Afghanistan: A quantitative study based on Technology Acceptance Model

PART I: Demographic Information

This data sheet will be used to collect none identifiable information of the respondent.

<u>PART II</u>: Cloud Computing Adoption in Afghanistan

Below are statements about Cloud Computing technology. Please indicate whether you agree or disagree with each statement by selecting the appropriate number on the scale of 1 (strongly disagree) to 5 (strongly agree) that most closely matches your perception of Cloud Computing technology.

Appendix B: NIH Human Subject Research Certificate of Completion

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **GEORGE NASSIF** successfully completed the NIH Web-based training course "Protecting Human Research Participants".

Date of completion: 05/15/2017.

Certification Number: 2394255.

Appendix C: Permission For Use of the Survey Instrument

Subject: Using survey instrument of study
To: "obink < >
Date: Saturday, November 3, 2018, 8:42 AM

Dr. Williams Obinkyereh,

I hope this email finds you well and in great shape,

I am George Nassif, a DIT student at Walden University. I am through my thesis of study concerning cloud computing adoption in developing countries. As being very successful reflecting a good findings of Ghana cloud computing case, I have selected your study to use the same survey instrument for mine. I wish you do accept so and you provide me with your full permission to proceed.

I will be waiting for your feedback, as I am thankful appreciating your good will to help.

George Nassif
DIT at Walden University

From: Williams T Obinkyereh < >
Date: Monday, November 3, 2018, 7:08 PM

Hello George Nassif,

I am glad you have read my research paper and found my research instrument very relevant to your research. You have therefore ask for the permission to use the research instrument in your own research. I am granting you permission through this email to use my research instrument for your own thesis. I wish you Good Luck in your thesis.

Your Faithfully.

Dr. Williams Obinkyereh

Appendix E: Email Invitation to Participate in Research

Date: [Insert Date]

Re: Invitation to Participate in a Research Study

Dear Sir/Madam,

I am George Nassif, a Doctor of Information Technology student at Walden University, Minneapolis, Minnesota, USA. I am inviting you to participate in this research study that would identify the relationship of four factors of perception of yours: (a) security, (b) privacy, (c) complexity, and (d) internet connectivity, with your intention to adopt cloud computing services. The population for the study is IT working solution architects and professionals with at least 3 years of experience for small and medium-sized enterprises (SMEs) located in Afghanistan. You are being invited because you are a member of the Information Technology professionals, and your experience, knowledge, and visions will allow this research study to analyze the real perception of information technology professionals' decision to adopt cloud computing technology in Afghanistan. The name of your organization is not required.

The survey will be web-based compiled on the public SurveyMonkey® to collect the data, and it only require 15 to 20 minutes of your time. Please, as soon as you read carefully the first page of the survey, the informed consent, click the checkbox confirming your approval prior to proceeding the survey.

To attend to the survey, double click on the URL below:

https://www.surveymonkey.com/user/sign-in/?ep=%2Fhome%2F%3Fut_source%3Dheader

Best Regards

George Nassif

Doctoral Candidate at Walden University

Appendix F: Invitation For Participants to View Study Results

Recently, you were invited to take part in a research study about adopting cloud computing services in Afghanistan. This email is to inform you that the analysis is complete and posted on https://Onedrive.georgenassif.com/doctoralstudy. Your privacy is of the utmost importance, which is why measures were taken to ensure no personally identifiable information was collected or reported. There is not any obligation for reviewing the results or partaking in any further actions.

I thank you for your time,

George Nassif
Doctoral Candidate at Walden University

Appendix G: Letter of Cooperation

جمهوری اسلامی افغانستان
وزارت تجارت و صنایع

د افغانستان اسلامی جمهوریت
د سوداګرۍ او صنایعو وزارت

Islamic Republic Of Afghanistan
Ministry Of Commerce & Industries
General Directorate Of Central Business Registry & Intellectual Property
ریاست عمومی ثبت مرکزی و ملکیت های فکری
مدیریت اجرائیه

تاریخ:

شماره:

Letter of Cooperation from a Research Partner

01/05/2019

Dear George Nassif,

Based on my review of your research proposal, I give permission to MOCI concerned staff to support you with the Afghan enterprises information list, available in MOCI registry, to conduct your study entitled Cloud computing adoption in Afghanistan: A quantitative study based on Technology Acceptance Model. As part of this study, I authorize you the use of our information to read, filter, and extract the right information required to fulfill the need of your study. However, MOCI Individuals' participation for any required support will be voluntary and at their own discretion.

We understand that MOCI's responsibilities include: Provide you with the list of small and medium sized enterprises operating in Afghanistan and registered into MOCI registry, explain the content data, support to filter out specific data if required. We reserve the right to discontinue or withdraw supporting you during the study at any time if our circumstances change.

I understand that the student will be naming MOCI and explaining about the support received in the doctoral project report that is published in Proquest.

I confirm that I am authorized to approve research in this setting and that this plan complies with the organization's policies.

I understand that the data collected will remain entirely confidential and may not be provided to anyone outside of the student's supervising faculty/staff without permission from the Walden University IRB.

Sincerely,

Tariq Ahmad Sarafaraz
Director General

آدرس : عقب چمن حضوری، چوار ریاست نمایشگاه، مقابل لیسه استقلال بیناب
Phone: +93752041772

Appendix H: Demographic Frequency Statistics

Table H1

Gender of Participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	113	93.4	93.4	93.4
	Female	8	6.6	6.6	100.0
	Total	121	100.0	100.0	

Table H2

Age of Participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24	7	5.8	5.8	5.8
	25-34	74	61.2	61.2	66.9
	35-44	30	24.8	24.8	91.7
	45-54	9	7.4	7.4	99.2
	55-64	1	.8	.8	100.0
	Total	121	100.0	100.0	

Table H3

IT Experience of Participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than one year	4	3.3	3.3	3.3
	1 to 5 years	23	19.0	19.0	22.3
	5 to 10 years	42	34.7	34.7	57.0
	More than 10 years	52	43.0	43.0	100.0
	Total	121	100.0	100.0	

Appendix I: Reliability Analysis

Table I1

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.532[a]	.283	.246	.60012	.283	7.517	6	114	.000

a. Predictors: (Constant), W_PEC, W_PEU, W_PEP, W_PU, W_PEN, W_PES

ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	16.243	6	2.707	7.517	.000[b]
	Residual	41.056	114	.360		
	Total	57.299	120			

a. Dependent Variable: W_IA

b. Predictors: (Constant), W_PEC, W_PEU, W_PEP, W_PU, W_PEN, W_PES

Perceived Usefulness

Table I2

Perceived Usefulness Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.931	.939	3

Table I3

Perceived Usefulness Item Statistics

PU-Item	Mean	Standard Deviation	N
PU1-Using Cloud Computing technology would make it easier to do my job.	4.1157	.69750	121
PU2-Cloud Computing technology would be useful for my job	4.1240	.61333	121
PU3-Using Cloud Computing technology would increase the productivity	4.2231	.68905	121

Table I4

Perceived Usefulness Inter-Item Correlation Matrix

	PU1	PU2	PU3
PU1-Using Cloud Computing technology would make it easier to do my job.	1.000	.834	.838
PU2-Cloud Computing technology would be useful for my job	.834	1.000	.836
PU3-Using Cloud Computing technology would increase the productivity	.838	.836	1.000

Table I5

Perceived Usefulness Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PU1-Using Cloud Computing technology would make it easier to do my job.	7.3884	4.106	.873	.762	.910

PU2-Cloud Computing technology would be useful for my job	7.2314	5.463	.871	.759	.899
PU3-Using Cloud Computing technology would increase the productivity	7.1157	5.237	.873	.763	.892

Perceived Ease of Use

Table I6

Perceived Ease of Use Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.760	.762	4

Table I7

Perceived Ease of Use Item Statistics

PEU-Item	Mean	Standard Deviation	N
PEU1-Interaction with Cloud Computing technology would be clear to understand	2.9347	1.03066	121
PEU2-Navigating Cloud Computing technology would be easy	3.2645	.98969	121
PEU3-Cloud Computing technology will be easy to learn to use	3.4132	1.0382	121
PEU4-Cloud Computing technology will make it easy to perform a task	3.1901	1.15696	121

Table I8

Perceived Usefulness Inter-Item Correlation Matrix

	PEU1	PEU2	PEU3	PEU4
PEU1-Interaction with Cloud Computing technology would be clear to understand	1.000	.254	.321	.765
PEU2-Navigating Cloud Computing technology would be easy	.254	1.000	.762	.189
PEU3-Cloud Computing technology will be easy to learn to use	.321	.762	1.000	.373
PEU4-Cloud Computing technology will make it easy to perform a task	.765	.189	.373	1.000

Table I9

Perceived Ease of Use Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PEU1-Interaction with Cloud Computing technology would be clear to understand	9.8678	6.182	.588	.603	.688
PEU2-Navigating Cloud Computing technology would be easy	9.5372	6.801	.480	.608	.744
PEU3-Cloud Computing technology will be easy to learn to use	9.3884	6.156	.611	.640	.676
PEU4-Cloud Computing technology will make it easy to perform a task	9.6116	5.790	.563	.629	.705

Perceived Privacy

Table I10

Perceived Privacy Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items

.694	.698	4

Table I11

Perceived Privacy Item Statistics

PeP-Item	Mean	Standard Deviation	N
PeP1-I feel my personal information is not protected on the cloud.	3.9008	.83071	121
PeP2-I feel my company's customers' personal information is not protected on the cloud.	3.8926	.80417	121
PeP3-I feel privacy on Cloud Computing technologies is more protected than it is on traditional computing method.	1.5289	.53885	121
PeP4-I would be concerned about Cloud Computing Privacy.	4.1983	.66608	121

Table I12

Perceived Privacy Inter-Item Correlation Matrix

PeP-Item	PeP1	PeP2	PeP3	PeP4
PeP1-I feel my personal information is not protected on the cloud.	1.000	.782	.207	.186
PeP2-I feel my company's customers' personal information is not protected on the cloud.	.782	1.000	.189	.374
PeP3-I feel privacy on Cloud Computing technologies is more protected than it is on traditional computing method.	.2207	.189	1.000	.349
PeP4-I would be concerned about Cloud Computing Privacy.	.186	.374	.349	1.000

Table I13

Perceived Privacy Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PeP1-I feel my personal information is not protected on the cloud.	9.6198	2.104	.598	.623	.508
PeP2-I feel my company's customers' personal information is not protected on the cloud.	9.6281	2.086	.647	.635	.468
PeP3-I feel privacy on Cloud Computing technologies is more protected than it is on traditional computing method.	11.9917	3.342	.295	.147	.701
PeP4-I would be concerned about Cloud Computing Privacy.	9.3223	3.020	.333	.187	.686

Perceived Security

Table I14

Perceived Security Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.824	.787	4

Table I15

Perceived Security Item Statistics

PeS-Item	Mean	Standard Deviation	N
PeS4-I feel confident to use Cloud Computing technology	3.1348	1.17324	121
PeS1-I feel that Cloud Computing technology is secure	4.3058	.56082	121

PeS2-I would be concerned about Cloud Computing Security	2.8760	1.18019	121
PeS3-I feel that Cloud Computing technologies are more secure than traditional computing method	3.0661	1.16000	121

Table I17

Perceived Security Inter-Item Correlation Matrix

	PeS1	PeS2	PeS3	PeS4
PeS1-I feel that Cloud Computing technology is secure	1.000	.090	.757	.776
PeS2-I would be concerned about Cloud Computing Security	.090	1.000	.209	.212
PeS3-I feel that Cloud Computing technologies are more secure than traditional computing method	.757	.209	1.000	.840
PeS4-I feel confident to use Cloud Computing technology	.776	.212	.840	1.000

Table I18

Perceived Security Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PeS1-I feel that Cloud Computing technology is secure	10.2479	5.905	.758	.647	.725
PeS2-I would be concerned about Cloud Computing Security	9.0744	10.636	.184	.069	.919
PeS3-I feel that Cloud Computing technologies are more secure than traditional computing method	10.5041	5.552	.841	.736	.678
PeS4-I feel confident to use Cloud Computing technology	10.3140	5.584	.856	.755	.670

Perceived Connectedness

Table I19

Perceived Connectedness Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.771	.766	4

Table I20

Perceived Connectedness Item Statistics

PeN-Item	Mean	Standard Deviation	N
PeN1-Cloud Computing technology is easy to access.	4.0909	.64550	121
PeN2-Internet connection is readily available to access Cloud Computing.	2.7851	1.22615	121
PeN3-Internet quality is good to have stable access to Cloud Computing systems.	2.8182	1.27802	121
PeN4-There is required infrastructure to access Cloud Computing technology.	3.9917	.80100	121

Table I21

Perceived Connectedness Inter-Item Correlation Matrix

PeN-Item	PeN1	PeN2	PeN3	PeN4
PeN1-Cloud Computing technology is easy to access.	1.000	.393	.384	.294
PeN2-Internet connection is readily available to access Cloud Computing.	.393	1.000	.868	.268

PeN3-Internet quality is good to have stable access to Cloud Computing systems.	.384	.868	1.000	.310
PeN4-There is required infrastructure to access Cloud Computing technology.	.356	.346	.357	1.000

Table I22

Perceived Connectedness Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PeN1-Cloud Computing technology is easy to access.	9.5950	7.910	.447	.213	.783
PeN2-Internet connection is readily available to access Cloud Computing.	10.9008	4.423	.780	.759	.587
PeN3-Internet quality is good to have stable access to Cloud Computing systems.	10.8678	4.232	.777	.758	.592
PeN4-There is required infrastructure to access Cloud Computing technology.	9.6942	7.531	.404	.185	.792

Perceived Complexity

Table I23

Perceived Complexity Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.714	.713	4

Table I24

Perceived Complexity Item Statistics

PeC-Item	Mean	Standard Deviation	N
PeC1-Cloud Computing technology is easy to access, login, and use.	3.7190	1.06633	121
PeC2-I would be concerned about the difficulty of using the Cloud Computing systems.	3.8678	.97418	121
PeC3-I feel the cloud computing systems are easier and simpler for use than the traditional systems.	3.4050	1.06128	121
PeC4-I feel comfortable to easily use the Cloud Computing systems.	3.3471	1.13071	121

Table I25

Perceived Complexity Inter-Item Correlation Matrix

PeC-Item	PeC1	PeC2	PeC3	PeC4
PeC1-Cloud Computing technology is easy to access, login, and use.	1.000	.301	.462	.275
PeC2-I would be concerned about the difficulty of using the Cloud Computing systems.	.301	1.000	.342	.269
PeC3-I feel the cloud computing systems are easier and simpler for use than the traditional systems.	.462	.342	1.000	.646
PeC4-I feel comfortable to easily use the Cloud Computing systems.	.275	.269	.646	1.000

Table I26

Perceived Complexity Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PeC1-Cloud Computing technology is easy to access, login, and use.	10.6198	6.204	.439	.238	.689

PeC2-I would be concerned about the difficulty of using the Cloud Computing systems.	10.4711	6.801	.379	.148	.719
PeC3-I feel the cloud computing systems are easier and simpler for use than the traditional systems.	10.9339	5.246	.680	.516	.538
PeC4-I feel comfortable to easily use the Cloud Computing systems.	10.9917	5.592	.525	.421	.638

Intention of Use of Technology

Table I27

Intention of Use of Technology Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.720	.717	4

Table I28

Intention of Use of technology Item Statistics

IUoT-Item	Mean	Standard Deviation	N
IA1-I am willing to use Cloud Computing technology for my work.	4.0992	.68805	121
IA2-I will like spending some time to learn how to use Cloud Computing technology for my work.	4.2479	.63615	121
IA3-I am willing to use Cloud Computing technology even if it is not secure	2.4876	1.29818	121
IA4-I am willing to use Cloud Computing technology even if my personal information is not protected	2.1488	1.20873	121

Table I29

Intention of Use of Technology Inter-Item Correlation Matrix

IA-Item	IA1	IA2	IA3	IA4
IA1-I am willing to use Cloud Computing technology for my work.	1.000	.438	.188	.172
IA2-I will like spending some time to learn how to use Cloud Computing technology for my work.	.438	1.000	-.006	.027
IA3-I am willing to use Cloud Computing technology even if it is not secure	.188	-.006	1.000	.835
IA4-I am willing to use Cloud Computing technology even if my personal information is not protected	.172	.027	.835	1.000

Table I30

Intention of Use of Technology Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IA1-I am willing to use Cloud Computing technology for my work.	8.8430	6.700	.444	.357	.693
IA2-I will like spending some time to learn how to use Cloud Computing technology for my work.	8.7355	7.496	.283	.296	.757
IA3-I am willing to use Cloud Computing technology even if it is not secure	10.4463	3.899	.684	.702	.528
IA4-I am willing to use Cloud Computing technology even if my personal information is not protected	10.8017	4.210	.685	.694	.524

Appendix J: Exploratory Factor Analysis

Table J1

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.049	18.699	18.699	5.049	18.699	18.699	3.786	14.023	14.023
2	3.186	11.798	30.498	3.186	11.798	30.498	3.604	13.347	27.370
3	2.608	9.657	40.155	2.608	9.657	40.155	2.908	10.772	38.141
4	2.082	7.710	47.865	2.082	7.710	47.865	2.625	9.724	47.865
5	1.960	7.257	55.123						
6	1.534	5.680	60.803						
7	1.379	5.108	65.911						
8	1.224	4.534	70.445						
9	1.051	3.891	74.336						
10	.952	3.527	77.863						
11	.890	3.296	81.159						
12	.836	3.095	84.254						
13	.649	2.404	86.658						
14	.612	2.268	88.926						
15	.554	2.052	90.978						
16	.468	1.734	92.712						
17	.351	1.301	94.013						
18	.271	1.005	95.018						
19	.229	.847	95.864						
20	.213	.789	96.653						
21	.192	.713	97.365						
22	.147	.546	97.911						
23	.139	.514	98.426						
24	.136	.502	98.927						
25	.115	.427	99.355						
26	.100	.371	99.725						
27	.074	.275	100.000						

Extraction Method: Principal Component Analysis.

Table J2

Rotated Component Matrix

	Component			
	1	2	3	4
PU1-Using Cloud Computing technology would make it easier to do my job.	.544		-.496	
PU2-Cloud Computing technology would be useful for my job	.550		-.468	
PU3-Using Cloud Computing technology would increase the productivity	.545		-.431	
PEU1-Interaction with Cloud Computing technology would be clear to understand		.412	.450	
PEU2-Navigating Cloud Computing technology would be easy		.448	.509	
PEU3-Cloud Computing technology will be easy to learn to use		.476	.541	
PEU4-Cloud Computing technology will make it easy to perform a task		.506		
PeP1-I feel my personal information is not protected on the cloud.		.686		
PeP2-I feel my company's customers' personal information is not protected on the cloud.		.609		
PeP3-I feel privacy on Cloud Computing technologies is more protected than it is on traditional computing method.				
PeP4-I would be concerned about Cloud Computing Privacy.				.459
PeS1-I feel that Cloud Computing technology is secure	.587			
PeS2-I would be concerned about Cloud Computing Security				.410
PeS3-I feel that Cloud Computing technologies are more secure than traditional computing method	.551			.503
PeS4-I feel confident to use Cloud Computing technology	.595			.536
PeN1-Cloud Computing technology is easy to access.	.499			
PeN2-Internet connection is readily available to access Cloud Computing.	.621			
PeN3-Internet quality is good to have stable access to Cloud Computing systems.	.615			
PeN4-There is required infrastructure to access Cloud Computing technology.	.463			
PeC1-Cloud Computing technology is easy to access, login, and use.	.402			
PeC2-I would be concerned about the difficulty of using the Cloud Computing systems.				
PeC3-I feel the cloud computing systems are easier and simpler for use than the traditional systems.	.571			
PeC4-I feel comfortable to easily use the Cloud Computing systems.	.441			.493
IA1-I am willing to use Cloud Computing technology for my work.	.494		.503	
IA2-I will like spending some time to learn how to use Cloud Computing technology for my work.	.410		.408	

IA3-I am willing to use Cloud Computing technology even if it is not secure	.451
IA4-I am willing to use Cloud Computing technology even if my personal information is not protected	.468

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Appendix K: Correlations

Table K1

Pearson Correlation

		MEAN.PU	MEAN.PEU	MEAN.PEP	MEAN.PES	MEAN.PEN	MEAN.PEC	MEAN.IA
MEAN.PU	Pearson Correlation	1	.062	-.086	.180*	.211*	.336**	.129
	Sig. (2-tailed)		.501	.349	.049	.020	.000	.160
	N	121	121	121	121	121	121	121
MEAN.PEU	Pearson Correlation	.062	1	.190*	-.062	.172	.015	.018
	Sig. (2-tailed)	.501		.037	.496	.060	.871	.844
	N	121	121	121	121	121	121	121
MEAN.PEP	Pearson Correlation	-.086	.190*	1	-.241**	-.179*	.115	-.271**
	Sig. (2-tailed)	.349	.037		.008	.050	.207	.003
	N	121	121	121	121	121	121	121
MEAN.PES	Pearson Correlation	.180*	-.062	-.241**	1	.209*	.241**	.249**
	Sig. (2-tailed)	.049	.496	.008		.022	.008	.006
	N	121	121	121	121	121	121	121
MEAN.PEN	Pearson Correlation	.211*	.172	-.179*	.209*	1	.344**	.357**
	Sig. (2-tailed)	.020	.060	.050	.022		.000	.000
	N	121	121	121	121	121	121	121
MEAN.PEC	Pearson Correlation	.336**	.015	.115	.241**	.344**	1	.125
	Sig. (2-tailed)	.000	.871	.207	.008	.000		.172
	N	121	121	121	121	121	121	121
MEAN.IA	Pearson Correlation	.129	.018	-.271**	.249**	.357**	.125	1
	Sig. (2-tailed)	.160	.844	.003	.006	.000	.172	
	N	121	121	121	121	121	121	121

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table K2

Statistics Bootstrap of Pearson Correlations

		MEAN.PU	MEAN.PEU	MEAN.PEP	MEAN.PES	MEAN.PEN	MEAN.PEC	MEAN.IA
MEAN.PU	Pearson Correlation	1	.062	-.086	.180*	.211*	.336**	.129
	Sig. (2-tailed)		.501	.349	.049	.020	.000	.160

	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		0	-.003	.001	.000	-.002	-.001	-.002
		Std. Error		0	.090	.091	.085	.082	.091	.091
		BCa 95% Confidence Interval	Lower	.	-.113	-.263	.010	.043	.134	-.059
			Upper	.	.229	.104	.347	.357	.516	.298
MEAN.PEU	Pearson Correlation			.062	1	.190*	-.062	.172	.015	.018
	Sig. (2-tailed)			.501		.037	.496	.060	.871	.844
	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		-.003	0	-.004	-.001	-.001	-.005	-.001
		Std. Error		.090	0	.096	.088	.093	.097	.101
		BCa 95% Confidence Interval	Lower	-.113	.	-.006	-.227	-.013	-.163	-.178
			Upper	.229	.	.361	.108	.354	.194	.212
MEAN.PEP	Pearson Correlation			-.086	.190*	1	-.241**	-.179*	.115	-.271**
	Sig. (2-tailed)			.349	.037		.008	.050	.207	.003
	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		.001	-.004	0	.000	.000	-.005	.001
		Std. Error		.091	.096	0	.075	.090	.100	.084
		BCa 95% Confidence Interval	Lower	-.263	-.006	.	-.378	-.345	-.083	-.418
			Upper	.104	.361	.	-.095	-.003	.293	-.097
MEAN.PES	Pearson Correlation			.180*	-.062	-.241**	1	.209*	.241**	.249**
	Sig. (2-tailed)			.049	.496	.008		.022	.008	.006
	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		.000	-.001	.000	0	.001	.004	-.001
		Std. Error		.085	.088	.075	0	.086	.079	.080
		BCa 95% Confidence Interval	Lower	.010	-.227	-.378	.	.033	.075	.088
			Upper	.347	.108	-.095	.	.377	.402	.403
MEAN.PEN	Pearson Correlation			.211*	.172	-.179*	.209*	1	.344**	.357**
	Sig. (2-tailed)			.020	.060	.050	.022		.000	.000
	N			121	121	121	121	121	121	121

	Bootstrap[c]	Bias		-.002	-.001	.000	.001	0	-.001	-.003
		Std. Error		.082	.093	.090	.086	0	.087	.090
		BCa 95% Confidence Interval	Lower	.043	-.013	-.345	.033	.	.163	.169
			Upper	.357	.354	-.003	.377	.	.504	.531
MEAN.PEC	Pearson Correlation			.336**	.015	.115	.241**	.344**	1	.125
	Sig. (2-tailed)			.000	.871	.207	.008	.000		.172
	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		-.001	-.005	-.005	.004	-.001	0	.003
		Std. Error		.091	.097	.100	.079	.087	0	.101
		BCa 95% Confidence Interval	Lower	.134	-.163	-.083	.075	.163	.	-.076
			Upper	.516	.194	.293	.402	.504	.	.325
MEAN.IA	Pearson Correlation			.129	.018	-.271**	.249**	.357**	.125	1
	Sig. (2-tailed)			.160	.844	.003	.006	.000	.172	
	N			121	121	121	121	121	121	121
	Bootstrap[c]	Bias		-.002	-.001	.001	-.001	-.003	.003	0
		Std. Error		.091	.101	.084	.080	.090	.101	0
		BCa 95% Confidence Interval	Lower	-.059	-.178	-.418	.088	.169	-.076	.
			Upper	.298	.212	-.097	.403	.531	.325	.

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

c. Unless otherwise noted, bootstrap results are based on 2000 bootstrap samples

Appendix L: Multiple Regression Analysis

Table L1

Summary Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.532	.283	.246	.60012	0.283	7.517	6	114	.000

Predictors: (Constant), W_PEU, W_PEP, W_PES, W_PEN, W_PEC, W_PU

Table L2

ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.668	4	3.667	8.101	.000b
	Residual	52.508	116	0.453		
	Total	67.176	120			

Dependent Variable: W_IA
Predictors: (Constant), W_PEC, W_PEP, W_PES, W_PEN

Table L3

Coefficients with Correlations and Collinearity Statistics

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.720	.474		5.736	.000	1.781	3.660					
	W_PEP	-.266	.101	-.230	-2.638	.010	-.466	-.066	-.269	-.240	-.209	.824	1.213
	W_PES	.151	.060	.218	2.504	.014	.032	.271	.327	.228	.199	.833	1.200
	W_PEN	.209	.058	.311	3.611	.000	.094	.324	.398	.320	.286	.846	1.182

W_PEC	.020	.077	.025	.265	.791	-.132	.173	.143	.025	.021	.729	1.372
W_PU	-.023	.053	-.036	-.425	.672	-.128	.083	.090	-.040	-.034	.855	1.170
W_PEU	.155	.072	.179	2.169	.032	.013	.297	.145	.199	.172	.918	1.089

a. Dependent Variable: W_IA

Table L4

Standard Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	2.720	.474		5.736	.000	1.781	3.660
	W_PEP	-.266	.101	-.230	-2.638	.010	-.466	-.066
	W_PES	.151	.060	.218	2.504	.014	.032	.271
	W_PEN	.209	.058	.311	3.611	.000	.094	.324
	W_PEC	.020	.077	.025	.265	.791	-.132	.173
	W_PU	-.023	.053	-.036	-.425	.672	-.128	.083
	W_PEU	.155	.072	.179	2.169	.032	.013	.297

a. Dependent Variable: W_IA

Table L5

Bootstrap for Coefficients Analysis

Model		B	Bootstrap[a]				
						BCa 95% Confidence Interval	
			Bias	Std. Error	Sig. (2-tailed)	Lower	Upper
1	(Constant)	2.720	.008	.423	.000	1.826	3.565
	W_PEP	-.266	-.002	.083	.001	-.420	-.112
	W_PES	.151	-.003	.057	.009	.040	.257
	W_PEN	.209	-.001	.068	.003	.075	.337
	W_PEC	.020	.001	.081	.803	-.132	.187
	W_PU	-.023	.001	.056	.681	-.134	.093
	W_PEU	.155	.000	.079	.048	-.002	.308

a. Unless otherwise noted, bootstrap results are based on 4000 bootstrap samples

Appendix M: Descriptive Statistics

Table M1

Summary of Frequencies Mean Variables

		MEAN.PU	MEAN.PEU	MEAN.PEP	MEAN.PES	MEAN.PEN	MEAN.PEC	MEAN.IA
N	Valid	121	121	121	121	121	121	121
	Missing	0	0	0	0	0	0	0
Mean		3.5675	3.3037	3.3802	3.3450	3.4215	3.5847	2.8926
Median		4.0000	3.5000	3.5000	3.5000	3.0000	3.7500	2.6667
Mode		4.00	4.00	3.25	2.50	3.00	4.00	2.00
Std. Deviation		1.07380	.90899	.51448	.85224	.78861	.77765	.90084
Variance		1.153	.826	.265	.726	.622	.605	.812
Skewness		-.832	-.566	-.739	-.175	.631	-.383	.320
Std. Error of Skewness		.220	.220	.220	.220	.220	.220	.220
Kurtosis		-.575	-.430	1.034	-.722	-.713	-.242	-.763
Std. Error of Kurtosis		.437	.437	.437	.437	.437	.437	.437
Range		4.00	4.00	2.50	3.25	3.25	3.75	4.00
Minimum		1.00	1.00	1.75	1.75	1.75	1.25	1.00
Maximum		5.00	5.00	4.25	5.00	5.00	5.00	5.00
Sum		431.67	399.75	409.00	404.75	414.00	433.75	350.00

Tables M2

Descriptive Statistics Mean Variables

	N	Range	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
MEAN.PU	121	4.00	1.00	5.00	431.67	3.5675	1.07380	1.153	-.832	.220	-.575	.437
MEAN.PEU	121	4.00	1.00	5.00	399.75	3.3037	.90899	.826	-.566	.220	-.430	.437
MEAN.PEP	121	2.50	1.75	4.25	409.00	3.3802	.51448	.265	-.739	.220	1.034	.437
MEAN.PES	121	3.25	1.75	5.00	404.75	3.3450	.85224	.726	-.175	.220	-.722	.437
MEAN.PEN	121	3.25	1.75	5.00	414.00	3.4215	.78861	.622	.631	.220	-.713	.437
MEAN.PEC	121	3.75	1.25	5.00	433.75	3.5847	.77765	.605	-.383	.220	-.242	.437

MEAN.IA	121	4.00	1.00	5.00	350.00	2.8926	.90084	.812	.320	.220	-.763	.437
Valid N (listwise)	121											

MEAN.PU

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	1	.8	.8	.8
	1.67	19	15.7	15.7	16.5
	2.00	4	3.3	3.3	19.8
	2.33	2	1.7	1.7	21.5
	2.67	3	2.5	2.5	24.0
	3.00	5	4.1	4.1	28.1
	3.33	3	2.5	2.5	30.6
	3.67	8	6.6	6.6	37.2
	4.00	42	34.7	34.7	71.9
	4.33	17	14.0	14.0	86.0
	4.67	8	6.6	6.6	92.6
	5.00	9	7.4	7.4	100.0
	Total	121	100.0	100.0	

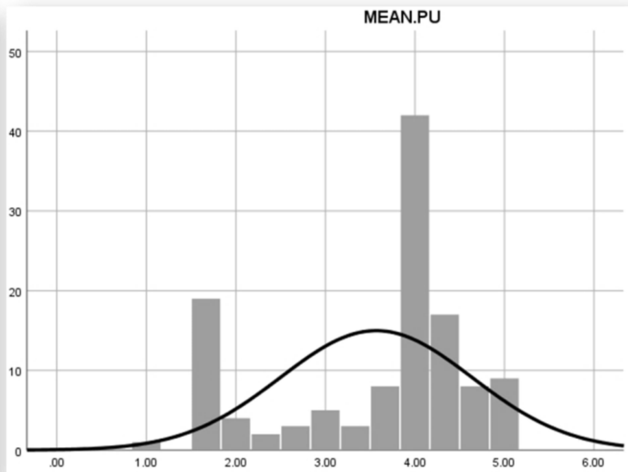

Figure M1. Perceived usefulness frequencies statistics and histogram

MEAN.PEU

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	3	2.5	2.5	2.5
	1.50	1	.8	.8	3.3
	2.00	19	15.7	15.7	19.0
	2.25	2	1.7	1.7	20.7
	2.50	7	5.8	5.8	26.4
	2.75	3	2.5	2.5	28.9
	3.00	8	6.6	6.6	35.5
	3.25	9	7.4	7.4	43.0
	3.50	11	9.1	9.1	52.1
	3.75	17	14.0	14.0	66.1
	4.00	27	22.3	22.3	88.4
	4.25	5	4.1	4.1	92.6
	4.50	5	4.1	4.1	96.7
	4.75	1	.8	.8	97.5
	5.00	3	2.5	2.5	100.0
	Total	121	100.0	100.0	

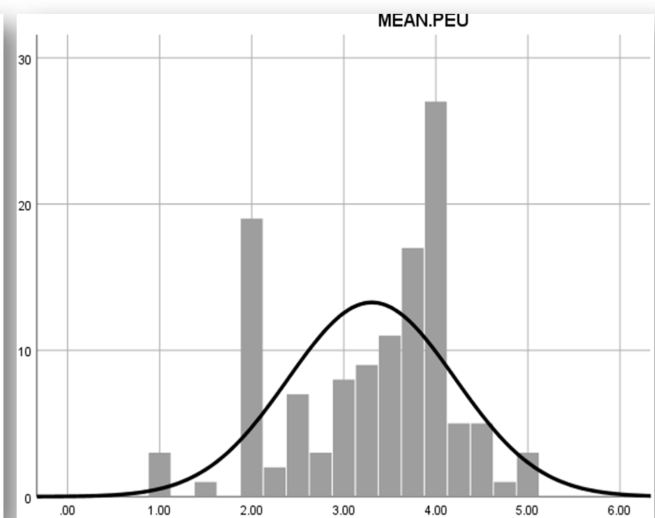

Figure M2. Perceived ease of use frequencies statistics and histogram

MEAN.PEP

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.75	1	.8	.8	.8
	2.00	3	2.5	2.5	3.3
	2.25	3	2.5	2.5	5.8
	2.50	4	3.3	3.3	9.1
	2.75	4	3.3	3.3	12.4
	3.00	9	7.4	7.4	19.8
	3.25	34	28.1	28.1	47.9
	3.50	28	23.1	23.1	71.1
	3.75	17	14.0	14.0	85.1
	4.00	9	7.4	7.4	92.6
	4.25	9	7.4	7.4	100.0
	Total	121	100.0	100.0	

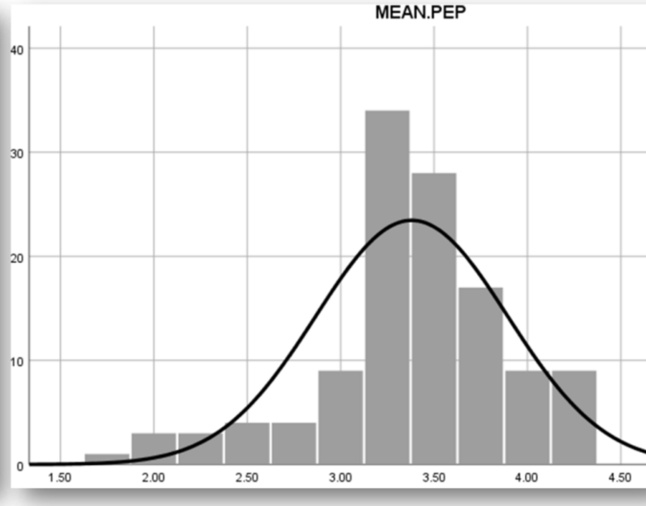

Figure M3. Perceived privacy frequencies statistics and histogram

MEAN.PES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.75	10	8.3	8.3	8.3
	2.00	2	1.7	1.7	9.9
	2.50	20	16.5	16.5	26.4
	2.75	7	5.8	5.8	32.2
	3.00	5	4.1	4.1	36.4
	3.25	13	10.7	10.7	47.1
	3.50	17	14.0	14.0	61.2
	3.75	9	7.4	7.4	68.6
	4.00	14	11.6	11.6	80.2
	4.25	12	9.9	9.9	90.1
	4.50	6	5.0	5.0	95.0
	4.75	2	1.7	1.7	96.7
	5.00	4	3.3	3.3	100.0
	Total	121	100.0	100.0	

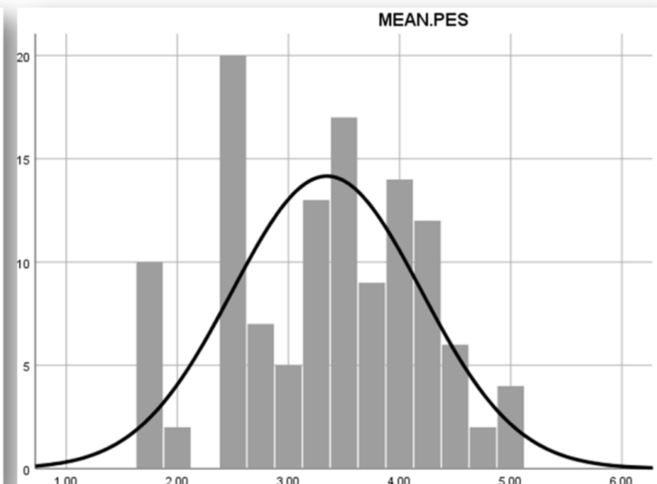

Figure M4. Perceived security frequencies statistics and histogram

MEAN.PEN

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.75	1	.8	.8	.8
	2.00	1	.8	.8	1.7
	2.25	2	1.7	1.7	3.3
	2.50	5	4.1	4.1	7.4
	2.75	16	13.2	13.2	20.7
	3.00	47	38.8	38.8	59.5
	3.25	4	3.3	3.3	62.8
	3.50	4	3.3	3.3	66.1
	3.75	3	2.5	2.5	68.6
	4.00	8	6.6	6.6	75.2
	4.25	8	6.6	6.6	81.8
	4.50	10	8.3	8.3	90.1
	4.75	4	3.3	3.3	93.4
	5.00	8	6.6	6.6	100.0
	Total	121	100.0	100.0	

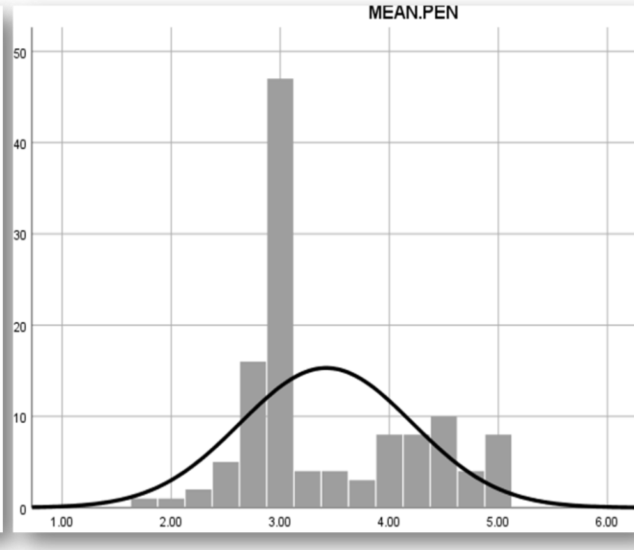

Figure M5. Perceived connectedness frequencies statistics and histogram

MEAN.PEC

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.25	1	.8	.8	.8
	1.75	1	.8	.8	1.7
	2.00	2	1.7	1.7	3.3
	2.25	5	4.1	4.1	7.4
	2.50	5	4.1	4.1	11.6
	2.75	9	7.4	7.4	19.0
	3.00	13	10.7	10.7	29.8
	3.25	10	8.3	8.3	38.0
	3.50	10	8.3	8.3	46.3
	3.75	14	11.6	11.6	57.9
	4.00	23	19.0	19.0	76.9
	4.25	9	7.4	7.4	84.3
	4.50	9	7.4	7.4	91.7
	4.75	6	5.0	5.0	96.7
	5.00	4	3.3	3.3	100.0
	Total	121	100.0	100.0	

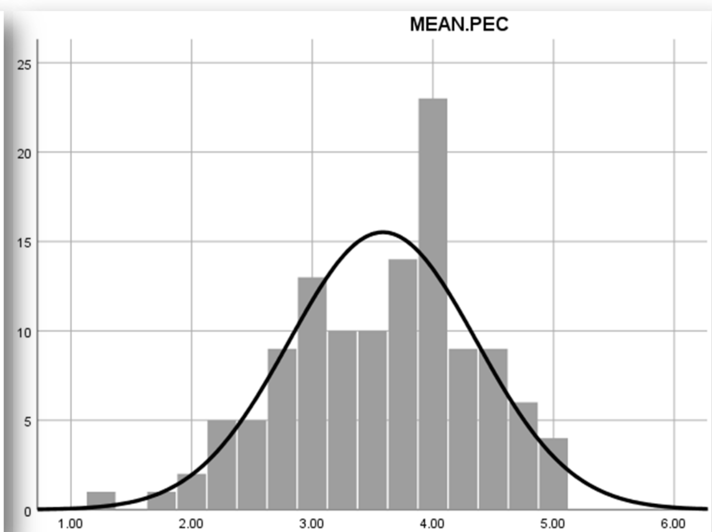

Figure M6. Perceived complexity frequencies statistics and histogram

MEAN.IA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	1	.8	.8	.8
	1.33	2	1.7	1.7	2.5
	1.67	7	5.8	5.8	8.3
	2.00	23	19.0	19.0	27.3
	2.33	18	14.9	14.9	42.1
	2.67	12	9.9	9.9	52.1
	3.00	9	7.4	7.4	59.5
	3.33	16	13.2	13.2	72.7
	3.67	9	7.4	7.4	80.2
	4.00	15	12.4	12.4	92.6
	4.33	5	4.1	4.1	96.7
	4.67	1	.8	.8	97.5
	5.00	3	2.5	2.5	100.0
	Total	121	100.0	100.0	

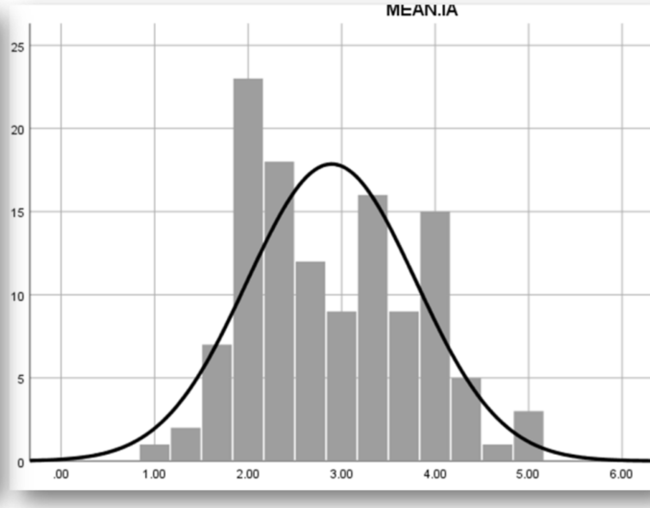

Figure M7. Behavioral intention frequencies statistics and histogram.